Developing an environmental calculator for application in the beef industry

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Declaration

I, Alasdair James Sykes, do hereby declare that

a) This thesis was composed by myself
b) The work contained herein is my own, except where clearly stated
c) This work has not been submitted for any other degree or professional qualification
d) Publications included in this thesis are my own work

Signed:

Date of signature:

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Table of contents

List of figures

List of tables

List of equations

Thesis abstract

Global greenhouse gas (GHG) emissions from livestock production contribute 18% to total anthropogenic emissions. Emissions from beef and dairy represent three quarters of this figure, and beef production emissions have risen by an estimated 59% in the past half century in response to increasing global population and wealth. In line with international climate commitments, there exists pressure for beef production systems to increase the emissions efficiency of production, and life cycle assessment (LCA) studies have proved a powerful tool to this end. Application of this knowledge to policy is hampered by the heterogeneity of agricultural systems, however, and farm-level GHG accounting tools contribute a flexible, bottom-up solution to this. A variety of such tools are available, but a number of issues hinder their uptake. This thesis therefore set out to a) identify the most important issues affecting the efficacy and uptake of extant farm-level GHG accounting tools and b) develop a farm-level model (AgRE Calc) to address these issues.

A review and test of existing tools found that differences in scope and methodology cause substantial differences in results calculated from common input datasets, an issue exacerbated by the methodological opacity of many tools. The empirical test conducted here provides insight into this, and also highlights the need for such tools to maintain simplicity in input data requirements, whilst maximising flexibility and detail in the output. To this end, the impact of cattle ration composition on modelled emissions was identified as a key parameter. The AgRE Calc model was developed to improve this aspect of the methodology, and used to carbon footprint data from a lifetime experiment focusing on beef finishing strategies and diets. Results of this study suggested that high quality grass-based diets have the potential to be as efficient as housed finishes. Additionally, the importance of good-quality, low-granularity activity data to the precision of the footprint was identified, as was the potential for variability in performance within treatments.

The study also highlighted the pivotal role of grazing quality in emissions intensity of production. Literature review found that practitioners and models typically broadly estimate this parameter; this approach lacks accuracy and flexibility, so a novel methodology was defined to enable empirical estimation of this variable. Utilising simplistic input data already required by AgRE Calc, a regression model was developed to predict grazed forage digestibility in relation to sward age and nitrogen fertilisation levels. The model predicts decreasing digestibility, resulting in lower performance and higher enteric emissions, as swards age and fertilisation levels decrease. Monte Carlo simulation was also used to provide an estimate of the uncertainty surrounding this variable, and the results suggest that manipulation of pasture digestibility could be a useful mitigation strategy for emissions from extensive beef production.

Uncertainty in modelled emissions was a common thread in these studies, and this was explored in more detail. AgRE Calc was developed for a Monte Carlo-based assessment

of epistemic uncertainty within farm-level models. The resulting study found that uncertainty in N_2O and purchased feed emission factors was the greatest source of farm-level emissions uncertainty. These factors greatly reduce the certainty with which comparisons between intensive and extensive approaches can be made. As such, it is recommended that uncertainty assessment in future form a greater aspect of farm-level and LCA assessments for livestock, and the methods and data compiled as part of this thesis form a basis for accomplishing this through Monte Carlo simulation.

Together, these assessments provide a framework for the development of farm-level tools with a view to increasing their usability and relevance. A number of areas in which further progress can be made are identified, and the thesis argues for recognition of the niche filled by farm-level approaches by the developers of GHG accounting methodologies. As such, the thesis as a whole provides a thorough blueprint for advancement of farm-level modelling of GHG emissions, alongside a comprehensive synthesis of the state of the art.

Lay summary

The production of beef animals for meat is a practice which has been shown to be connected to significant emission of greenhouse gases (GHGs), and has further negative impacts on the wider environment. Beef production is also becoming much more widespread as a result of increasing demand, resulting from both a growing global population, and increasing income in many developing nations. It is largely accepted that a reduction in total production of beef would be an effective way to reduce the associated GHG emissions; however, projected demand for beef is such that production is likely to continue growing in the short- to medium-term. As such, it is widely recognised that there is a pressing need for beef production systems to become more efficient; in essence, the global beef industry must increase production while reducing emissions.

However, governments seeking to reduce the emissions per unit of beef production (the 'emissions intensity') face a considerable challenge. A large part of this stems from the fact that beef production systems and practices can be very different, and this variation occurs not just between world regions or nations, but also over much smaller scales. This makes the systems difficult to understand at a national level, and so mitigation strategies are difficult to legislate for. In addition to being heterogeneous, these systems are typically highly complex, with GHG emissions coming from many different sources. Direct sources (GHGs emitted from the farm itself) are largely the result of biological processes, which can be complex and difficult to understand. Indirect sources (GHGs emitted in the process of producing commodities used by the farm, such as feed or fertiliser) can be difficult to trace and quantify.

Creating a mathematical model of a beef production system is an informative and cost-effective way to understand how these systems produce emissions, and how they can be made more efficient. Many kinds of models can be applied to farm-level processes, but in order to be of greatest use in the challenge of reducing the emissions intensity of beef production, a model must have the following characteristics:

a) The model must be flexible, to capture the wide variety of beef production practices
b) The model must be broad enough to capture all of the sources of GHGs, direct and indirect, associated with beef production, so as to avoid missing the full picture or making false economies
c) The model must be simple enough that the input data required is not so complex or detailed that regular farms cannot provide it
d) The model must be detailed and precise enough that the results are of use to policy makers seeking to reduce beef emissions intensity.

Fig. LS.1 shows the scope of a typical farm-level model which has the potential to fulfil these criteria. Given the challenges identified, the aim of this thesis was to develop a farm-level model ('AgRE Calc') to better fit these criteria, and to further the ability of policy makers to mitigate for GHG emissions from beef systems.

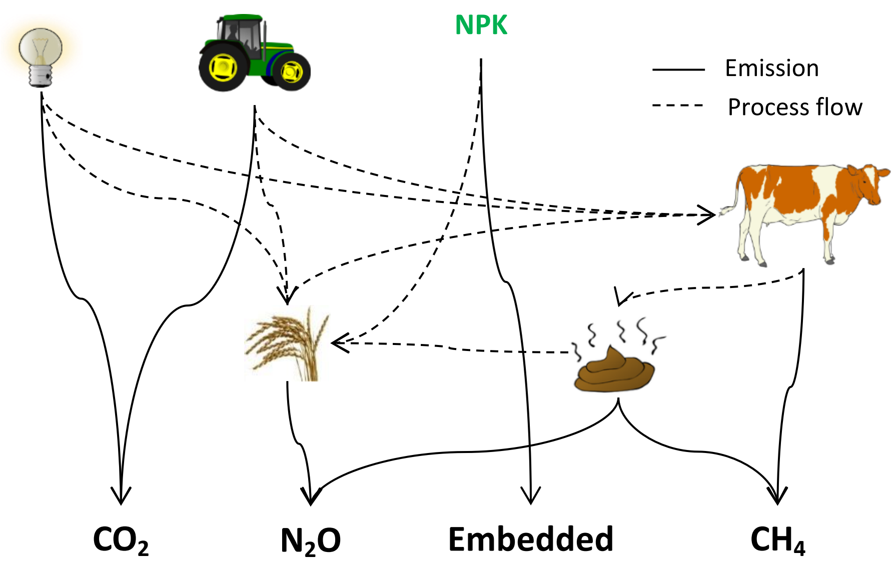

Fig. LS.1. Simplified scope diagram for a farm-level model of a livestock production system, showing sources of carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4) and embedded (indirect) emissions. The dashed arrows indicate how processes on the farm interact with one another.

The first step taken in developing the AgRE Calc model was to conduct a survey of other models for comparison, to identify areas of strength, weakness and potential for further development. The introduction to this thesis (chapter one) therefore incorporated a review of existing models and also considered some existing publications which have attempted to do this. It was identified that developers of farm-level models have followed a variety of routes towards quantifying GHG emissions, and that a lack of supporting documentation often makes it difficult to understand exactly how a model works. In effect, models risk becoming 'black boxes', where inputs are entered, and outputs are generated, with no opportunity for the user to understand how.

As a result, chapter two of this thesis focused on conducting a *quantitative* review of existing farm-level models. Input data from seven livestock farms was applied to five different tools (including AgRE Calc) to generate carbon footprints, and these were compared. This enabled the challenge of poor documentation, a major issue for several tools, to be overcome to some extent. The study found that tools produce varied results, and that scoping (inclusion or omission of different sources) and allocation (attribution of emissions from a source to a user, e.g. apportioning emissions from crop production to the livestock to which the crops are fed) are key issues for farm-level tools. The study concluded that while variation in tool methods may be to some extent inevitable, maintaining the transparency of the approach is crucial to allow users to understand the differences between tools, and the reasons for variations in the carbon footprint of a farm.

This study also highlighted some areas where the development of AgRE Calc would provide the greatest improvement to the model's usability. These were carried out in the third chapter of this thesis, and consisted of:

a) Improvement of the way that AgRE Calc accounts for the impact that the quality of cattle feed has on the emissions of methane from the bovine digestive system
b) Improvement of the way that AgRE Calc accounts for emissions from off-farm feed production
c) Development of the methods used in AgRE Calc to allow them to become internationally applicable, rather than usable only in the United Kingdom
d) Alteration and development of the model to allow it to estimate the uncertainty in emissions estimates

Following these developments, a study was undertaken, utilising the improved AgRE Calc model to carbon footprint a series of beef finishing systems (chapter four). This served the purpose of testing the efficacy of the improvements made to the model, and made use of available high quality input data to provide a comparison of intensive vs. extensive beef production. Intensive, often housed, production achieves fast rates of growth through use of high quality feeds and high levels of control over the animals' intake and behaviour; daily emissions are generally high, but a large amount of meat is produced quickly. Extensive production is typically grazing-based, and has the opposite effect; lower growth rates and slower production, but lower emissions on a daily basis. The relative merits of each system type are debatable, but in general, prevailing recent opinion has tended to favour intensification of beef systems. This study broadens that debate with the finding that the most GHG-efficient systems may be a combination of the two; systems which made use of grazing land, but which acted to improve the quality of that land and keep fine control over animal performance, emerged as the most efficient systems in the studied sample.

This result served to highlight the importance of the nutritional quality of grazing land in influencing the efficiency of beef production. This is not something which farm-level models, including AgRE Calc, are able to model effectively; it can be very variable and may change as a result of many influencing factors. For the study in chapter four, high-quality data from laboratory measurements enabled a clear comparison to be made, but this type of data is not usually something to which farmers would have access. As such, it made sense to develop an approach which would enable AgRE Calc to account, as much as possible, for variations affecting the nutritional quality of grazed grass. The fifth and sixth chapters of this thesis are dedicated to an exploration of this issue, and the development of a model which utilises available input data from AgRE Calc to estimate the nutritional quality of grazing land. The model shows that grazing land declines in quality with increasing time since renovation and decreasing nitrogen inputs, and enables AgRE Calc to account for emissions trade-offs related to changes in these variables. The model also provides a basis by which researchers can estimate uncertainty relating to this variable in future studies.

A great proportion of the research conducted up to this point in the thesis pointed to the importance of uncertainty in modelled estimates of farm-level emissions. This uncertainty stems largely from difficulties in a) ascertaining the accuracy of input data, b) estimating the impact of this data on emissions, and c) choosing a scope (set of emissions sources) and methodology for the study. The primary role of a farm-level model falls within point b) (estimating emissions), and so a study was designed which would allow this uncertainty within the AgRE Calc model to be quantified and analysed in the context of an emissions estimate of a typical beef system. The study showed that the majority of uncertainty lies within a few aspects of the model; these are associated with predicting nitrous oxide from land, methane from cattle, ration quality and 'upstream' emissions from the production of purchased livestock feed. The study detailed how these uncertainties could best be reduced by modellers with currently available methods, and how the developers of new GHG modelling methods could seek to address them.

The thesis as a whole forms a thorough appraisal of the current role and state of farm-level GHG modelling, and sets out an agenda for the way in which this can be improved and refined. The current and future role of farm-level GHG modelling tools in the context of the global challenge of reducing beef emissions is defined and discussed. The thesis provides a number of resources, databases, and methodologies which can be utilised to this end. The conclusion of the thesis provides a summary of current and gained knowledge for the users of farm-level tools, their developers, and the related scientific community whose collated knowledge forms the basis upon which these tools rely.

Chapter One

Developing an environmental calculator for application in the beef industry

1.1. Livestock agriculture in a global context

The global population is growing; this trend is projected to continue throughout the 21st century, translating into a global population of 11.2 billion by 2100 (Lutz et al., 2001; FAO, 2017). While slowing each year on a global level, population expansion is nonetheless accelerating in food-scarce, developing nations, where *per capita* income is also increasing (FAO, 2017). Demand for food is consequently projected to continue increasing, and the methods by which the growing population will feed itself are the subject of ongoing concern and debate (Bongaarts, 1994; Borlaug, 2000; Van Kernebeek et al., 2016). Socioeconomic development can induce rapid dietary change (Kastner et al., 2012), and, while cultures vary, demand for animal protein generally tracks the increase in *per capita* wealth (Sans & Combris, 2015). As such, global demand for meat is increasing both as a result of population increase and *per capita* demand, with the result that meat demand is anticipated to rise by 68% over 20 years (2011−2030) (FAO, 2011).

Climate change has been identified as the most potent threat facing the global economy (World Economic Forum, 2016), and public, scientific and political consensus generally reflects this sentiment (Lorenzoni & Pidgeon, 2006). In line with this, the Paris Agreement formalised a commitment to hold the increase in global average temperature to well below 2°C since pre-industrial times (Griscom et al., 2017). Achieving this commitment is certain to be extremely challenging (Peters et al., 2013), and will require significant reduction in greenhouse gas (GHG) emissions from all sectors. If rising demand for livestock protein is to be met, livestock agriculture therefore faces the dual challenge of reducing emissions while increasing production. This process has already begun; Opio et al. (2011) show the changes which global production has undergone in response to three decades of population and income growth. Livestock remains a significant contributor to the global GHG budget, however; global emissions from livestock production contributed 18% to total annual anthropogenic emissions in the first years of the 21st century (Steinfield et al., 2006). A growing global herd and high per-head emissions (Opio et al., 2013) means that cattle (i.e. beef and dairy production) form a significant proportion of this total, contributing almost three-quarters of total emissions (Caro et al., 2014). Over time, emissions from beef have risen by an estimated 59% over 50 years (Caro et al., 2016).

Production of calories from livestock is inherently a less efficient process than equivalent arable production (Cassidy et al., 2013; Davis & D'Odorico, 2015a). This low efficiency is a key factor in rendering livestock production, and its increase, of critical environmental concern (Opio et al., 2011). Greenhouse gas emissions per kg of production ('emissions intensity') vary between types of animal-derived protein; ruminant production systems, particularly beef, tend to be the least efficient (Eshel et al., 2014). There also exists considerable disparity in production efficiency within sectors, which provides opportunity for mitigation of emissions. Qualifying this on a global scale, Smith et al. (2008) identified a number of approaches by which livestock emissions or emissions intensities can be reduced. Three types of direct management practice were explored; improved feeding practices, dietary additives and longer term management and breeding practices to improve performance potential. In addition, practices relating to management of livestock manures, grazing land and cropland for feed production all had potential to further reduce the emissions associated with production.

In general terms, livestock agriculture in the developing world is characterised by low-input, low performance systems (Subak, 1999). Extractive farming practices (e.g. overgrazing) may reduce soil nutrient content and result in low producing pastures and croplands, as well as direct CO_2 emission from soils (Vågen et al., 2005). Progressive intensification of these low-input systems has occurred over the past century in many western nations, and has been shown to reduce emissions intensity through improvement of animal performance and offset of enteric methane emissions (e.g. Cardoso et al., 2016). The majority of current beef production is located in developing nations (Kastner et al., 2012), and this is also where the majority of efficiency gains can be made; these factors mean that developed nations, which have undergone historical improvement of their production systems, have a role as thought and practice leaders (e.g. Gerber et al., 2013a; Opio et al., 2013).

In addition to potential for efficiency gains, it is worth noting that the global livestock production sector could reduce its contribution to global emissions simply by reducing production; Steinfeld & Gerber (2010) point out that either approach is possible, since the current rapid change in livestock agriculture is driven only in part by growing populations, and to a larger extent by a growing middle class. In this sense, demand is manageable. With this in mind, it has been suggested that a move away from western-level reliance on animal protein may be necessary or inevitable; a number of studies (Cassidy et al., 2013; Davis & D'Odorico, 2015b; Davis et al., 2016; Gephart et al., 2016) demonstrate that apportioning human-edible arable crops away from the inherently inefficient livestock sector would be one way of mitigating environmental concerns and providing adequate food for a growing population. Land availability may also impose a limit on global meat consumption; Kastner et al. (2012) show that an area double the size of that currently cultivated would be required to feed a global peak population with an equivalent western diet. Even if this were physically possible, the environmental damage caused by this shift would likely be severe before this point was reached (e.g. Machovina et al., 2015). Based on this logic, there exists a school of thought which suggests that livestock production practices are inefficient to the extent that they are irreconcilable with sustainable agriculture; more recently, some influential viewpoints in the popular media have begun to reflect this sentiment (e.g. Andersen & Kuhn, 2014; Monbiot, 2017).

There is also some evidence to suggest that developed societies may voluntarily move away from reliance on livestock products over time (FAOstat, 2017), and trends such as vegetarianism or veganism may occur as societies become richer and better educated (Ruby & Heine, 2012). Despite this, however, there currently exists a pressing demand for meat which is likely to continue to increase in the short- to medium-term (FAO, 2011). Managing the demand for livestock products is an important approach towards maintaining food security and minimising environmental concerns (Steinfeld & Gerber, 2010), but the currently prominent role of livestock production in the global economy (Opio et al., 2011) suggests that this will be a relatively slow process. Demand for animal protein and predicted peak population are both demonstrably linked to demographic transition (Lutz et al., 2001; Simpson, 2014; Sans & Combris, 2015), and the critical phase of action to maintain the 2^{o}C limit falls ahead of this demand peak (Griscom et al., 2017). This thesis will be developed in this context; namely, the requirement to address the immediate requirement for improvement of efficiency within livestock production systems, whilst acknowledging that active management of demand for animal-based protein is an important strategy for long-term mitigation of environmental impacts from this sector, and for preservation of global food security at peak population.

1.2. The role of modelling in agricultural greenhouse gas mitigation

1.2.1. Rationale for modelling in agriculture

In order to define effective strategies for the mitigation of emissions, it is necessary to understand the system in question. Farming systems, particularly those involving livestock production, are complex; Janzen et al. (2006) make the observation that interactions, feedbacks and trade-offs between on-farm practices and processes are inevitable, necessitating the use of broad-scope, holistic modelling approaches in order to avoid false economies when defining mitigation practices. At an even simpler level, modelling represents a cost-effective approach to the question of quantifying system level emissions; whilst direct measurement is not impossible (e.g. Taylor et al., 2017), it is complex and costly, and fails to account holistically for upstream emissions, which can be important in trade-offs (Janzen et al., 2006). In enabling consideration of hypothetical systems and system changes, modelling approaches offer valuable support to farm and policy-level decision makers (Kipling et al., 2016).

Models of natural systems vary by type and application, but can broadly be divided into empirical and process-based models (Gibbons et al., 2006; Del Grosso et al., 2006).

Process-based models typically focus on representing underlying biological processes; by contrast, empirical models may ignore these underlying processes and instead focus on drawing conclusions based on observed data. Since most natural systems are inherently complex, accurately representing and quantifying underlying biological processes can be extremely challenging. Process-based models are therefore typically highly complex, and calibrating these models for different systems can be challenging, and is often prohibitively data-intensive (Hillier et al., 2011). Empirical models are typically much more simplified, and therefore less demanding of data. Whilst in some cases, these may lack the precision required for insightful analysis (Del Grosso et al., 2006), counterintuitively, empirical models may be more accurate in real-world applications (e.g. Landau et al., 1999). This occurs as the difficulties associated with validation of complex, multi-step process models can lead to considerable uncertainties; conversely, the simplification of these models to empirical approaches can reduce this potential for uncertainty propagation. Lower data requirements may also render empirical models easier to integrate into system-level studies (Gibbons et al., 2006). Process-based models provide a means to study and understand natural processes; by design, empirical approaches are utilitarian, and eschew this role in favour of practical application.

Whilst process-based models have found considerable application in agricultural systems, use of these models has tended to be specific to academic assessments focusing on a particular emissions source (e.g. Del Grosso et al., 2005, 2006; Kröbel et al., 2016; Zhang et al., 2017). For broader, system-level assays, simpler and more practical empirical models (which, to some extent, draw on the insights of process models) have tended to be utilised (e.g. Little et al., 2008; Hillier et al., 2011; MacLeod et al., 2013). The simplicity of these models permits a broader scope of assessment and generates a much lighter data demand.

1.2.2. The particular challenge of mitigating agricultural emissions

Under the Kyoto Protocol, most countries calculate an inventory of their GHG emissions. The methodology provided by the Intergovernmental Panel on Climate Change (IPCC) guidelines for national GHG reporting (IPCC, 1996, 2006) serves as a basis for the calculation of these inventories (see section 1.2.5). This assessment is conducted by sector at national level, and allows national governments to quantify and benchmark emissions in order to demonstrate compliance with internationally agreed targets. In the case of many industries, the methodology recommended by the IPCC for national level inventories (see section 1.2.5 for greater detail) provides enough detail for governments to effect top-down approaches to mitigate GHG emissions. Moran et al. (2011) observe that many high-emitting industries such as power generation involve relatively few centralised enterprises, and mitigation practices which are largely well understood and documented. Consequently, top-down approaches to development of optimal mitigation strategies can be effectively undertaken using models which make broad, sector-wide assumptions. Agriculture, by contrast, is much more heterogeneous, with diversity on local and regional scales. As such, mitigation of emissions from agricultural practices resists a top-down approach; broad-brush mitigation strategies are difficult to tune across a diverse range of practices. Adding to this, the relative complexity of many of the biological emissions pathways (e.g. soil-based nitrous oxide emissions, or methane from enteric fermentation) means that, to work around data constraints, national inventory methodologies may be simplified to the point where they do not provide enough precision to respond to system changes representing mitigation strategies (e.g. IPCC Tier 1 methodology for livestock; Dong et al., 2006). Finally, mitigation within the agricultural sector represents a challenge in that measures may involve a trade-off between emissions sources (e.g. Hünerberg et al., 2014). National inventories (e.g. Salisbury et al., 2014) calculate emissions on a source basis, rather than an end user basis, and so do not account holistically for trade-offs where a mix of direct and ‘upstream’ emissions are involved.

Life cycle assessment (LCA) offers a solution. This methodological framework provides a basis for the estimation and assessment of the environmental impacts associated with the life cycle of a product (Rebitzer et al., 2004). This approach can be broadly divided into two categories; attributional LCA, which aims to describe this environmentally relevant physical flows to and from the life cycle of a product, and consequential LCA, which aims to describe how these flows change in response to management (Ekvall et al., 2016). Most LCAs of livestock systems are attributional, and crucially differ from guidelines-based national inventories in that they account holistically for upstream emissions sources (e.g. agrochemical production). This typically renders approaches of this type more useful in the definition and assessment of mitigation options. However, the complexity of such systems typically means that LCAs focus on either one system type, or at most a limited range (e.g. Beauchemin et al., 2010; Cardoso et al., 2016). As such, it is reasonable to suggest that the same heterogeneity which negates the efficacy of top-down approaches in agricultural systems also represents a barrier to the application of the results of individual LCAs to policy. Policy makers seek to legislate for a broad and diverse sector, and results garnered from a single specific system or system type are difficult to generalise. Differences in aims, methods and scope represent a barrier to review-based and meta-analytical synthesis of results derived from LCA studies.

This landscape represents the niche in which farm-level GHG modelling tools exist. In order to overcome the challenges discussed above, such tools must be

a) Holistic in approach, in order to capture upstream emissions and associated trade-offs,
b) Precise and detailed enough to respond to nuanced changes in the modelled system,
c) Simple enough to not impose prohibitively high data input or calibration burden, and
d) Flexible enough to capture a wide range of scenarios

This thesis aims to develop the AgRE Calc fam-level GHG modelling tool in line with the above constraints, and to improve its ability to function as a tool for farm-level benchmarking and mitigation assessment within these boundaries. The remainder of this section (1.2.3 – 1.2.6) considers the technical aspects of modelling farm-level emissions and environmental impacts within the defined framework, in order to provide a synthesis of the current state of the art and a basis for the consideration of specific development objectives.

1.2.3. Sources and sinks of GHGs in livestock agriculture

Three major GHGs are emitted by the processes associated with livestock production. Almost all farm GHG calculators and LCAs assess these gases in some capacity, though frequently vary in terms of the exact sources and sinks assessed (Schils et al., 2007). These gases are methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2). There is also the potential for chlorofluorocarbon release, (e.g. from refrigeration equipment), though this is likely to be relatively limited in the majority of agricultural systems. A graphical representation of the sinks and sources of these gases is shown in Fig. 1.1.

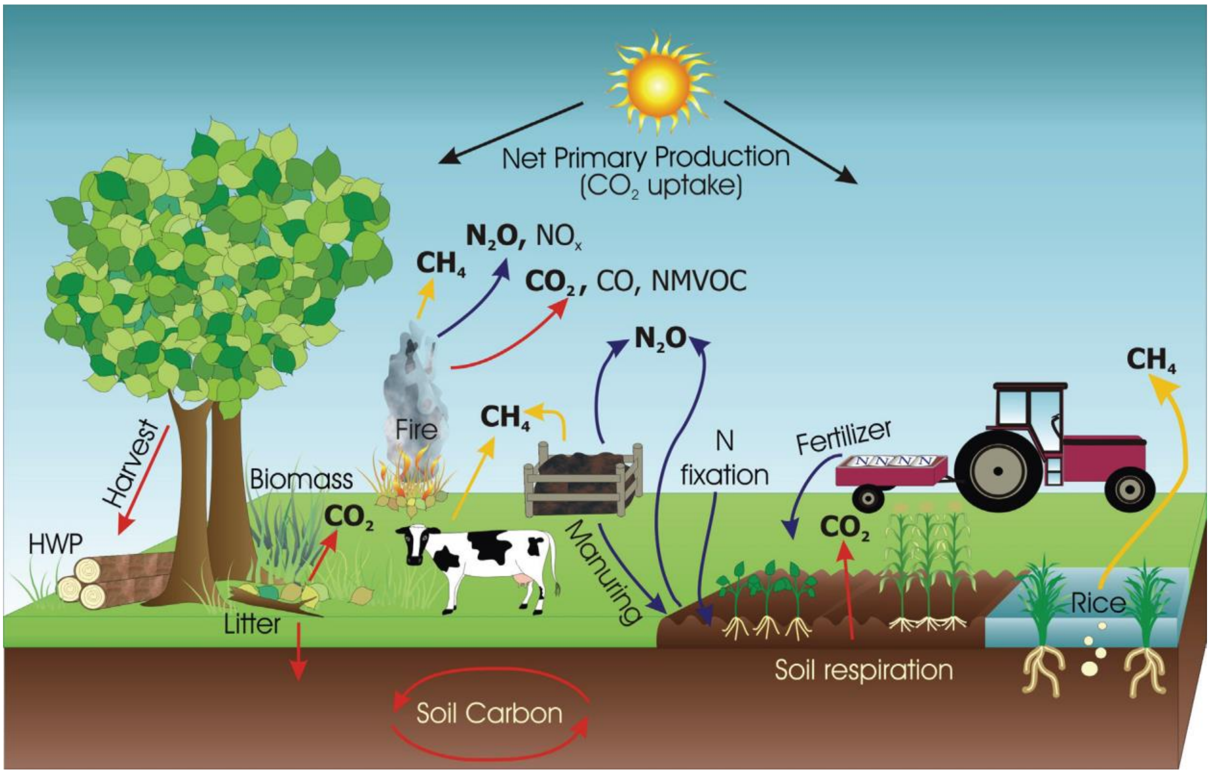

Fig. 1.1. A graphical representation of the major sources and sinks of GHGs in a stylised agricultural system. Figure shows the main pools and flows of greenhouse gases which must be considered in a farm-level GHG footprint (source: IPCC, 2006).

Enteric CH_4 is a by-product of the ruminant digestive system, and is known to be regulated by a number of factors, including feed intake, structure and nutrient composition (Cederberg et al., 2013). It is estimated that CH_4 emission typically accounts for around 6.5% of a ruminant's gross energy intake (Dong et al., 2006). Manure storage also contributes significantly to CH_4 emission; this is most notable in cattle and pig production systems (Cederberg et al., 2013). These are typically calculated according to IPCC (2006) Tier 2 guidelines; the IPCC provide a methane conversion factor for various systems and a range of annual temperatures. Accuracy can be improved where region-specific data is used (Cederberg et al., 2013).

Nitrous oxide is emitted from a variety of nitrogen sources. A major source is soil, which emits N_2O via the process of denitrification and, to a lesser extent, nitrification

(Cederberg et al., 2013). These processes are complex; emissions can be both direct and indirect, and can be affected by local conditions such as climate, soil type, soil structure and drainage as well as nitrogen fertiliser application, manure application and crop residue management. Consequently, N_2O emissions from managed grassland can vary widely; Rees et al. (2012) showed that emissions collected from a compilation of experiments on European arable land can vary from 0.04 to 21.2 kg N_2O-N ha^{-1} yr^{-1}. This variability and array of contributing factors combine to make N_2O emissions from soil amongst the hardest to assess accurately. Nitrous oxide can also be released directly from manure (Dong et al., 2006), meaning that livestock numbers, breeds and diets, together with manure excretion to pasture and management regimes can also impact emissions of this GHG.

Carbon dioxide is emitted on farm primarily from burning of fossil fuels; whilst land burning regimes may also contribute significantly in some areas, this is strictly controlled in the UK (Dong et al., 2006). Machinery and vehicle operation and heating of buildings are prime reasons for on-farm fossil fuel use; consequently, intensive systems tend to produce more CO_2 from this source (Cederberg et al., 2013). Electricity supplied for use on farm will come from a range of sources, and it is likely that a portion of these will be fossil fuel powered (Sainz, 2003).

Farms are not closed systems, and farm-level assessments must take stock of GHG emissions associated with inputs and outputs. These are termed 'embedded' emissions and are frequently made up of a range of GHGs; consequently, they are generally assessed at farm level in the form of CO_2 equivalents (CO_2-eq) (Gerber et al., 2013). Frequently included are emissions embedded in imported livestock feed/bedding, fertilisers, biocides and other agrochemicals (Gerber et al., 2013). It is also possible to assess embedded emissions associated with the construction of vehicles, machinery, buildings, and so on; some LCAs do this, though proportional allocation of these centralised embedded emissions to a specific product or even an annual whole-farm assessment is problematic.

System boundaries must also be defined for emissions relating to farm exports, whether this is a waste product, or a saleable by-product or main product. Exportation of by-products such as manure raises complex issues; a whole-farm assessment may choose to account for potential GHG emissions from this exported product, or may ignore that proportion which leaves the farm gate. Likewise, the same assessment may include or ignore embedded emissions from imported manure. How these boundaries are defined will impact, perhaps significantly, upon the overall results of such an assessment, and comparisons between differently scoped assessments must be made with care to avoid misleading conclusions.

A GHG sink is something which facilitates removal of a GHG from the atmosphere (Smith et al., 2008). These exist alongside many agricultural systems, in the form of cultivated and natural soils, field margins, hedgerows, woodland, and wetlands (Griscom et al., 2017). Whole-farm assessments will sometimes assess the CO_2 sequestration potential of these (e.g. Hillier et al., 2011). There are challenges associated with quantifying CO_2 removal by certain sinks, particularly where these are soil-based (e.g. Campbell & Paustian, 2015), and under certain management practices, soils can become net emitters of CO_2. There are also issues associated with the permanence and fate of forestry-based sinks; whilst quantifying CO_2 removal by forestry is comparatively simple, if the resulting biomass is burned or allowed to fully decompose, the net CO_2 sequestration is returned to zero (Cannell, 1999). Land use may also change as a result of agricultural practices; a land use change assessment examines the difference in sequestration or emission potential between the two land cover types (Gerber et al., 2013). This can improve sequestration rates (e.g. if an area of grassland is planted with trees), but can be negative (e.g. deforestation to create land for cropping) (Steinfield et al., 2006). Difficulties associated with this approach largely stem from a) defining the change in sequestration potential between land use types and b) defining a baseline land use from which to quantify changes.

1.2.4. Other environmental impacts of agriculture

Aside from the well documented effect of GHG emission, ammonia production from livestock is an important environmental concern. Around two-thirds of global ammonia release stems from the livestock sector, and this contributes heavily to acid rain, indirect GHG emissions, and eutrophication and acidification of ecosystems (Steinfield et al., 2006). Sensitive ecosystems are particularly affected, with damage also caused by nitrogen deposition or acidification of soils (Demmers et al., 1999). Measuring ammonia release from UK cattle buildings, Demmers et al. (1998) estimated 6.0kg NH_3 (500kg live weight)$^{-1}$ (190 days)$^{-1}$ for a slurry-based dairy unit and 3.7kg for a straw-bedded beef unit.

Building on this work, Misselbrook et al. (2000) put forward an estimated UK agriculture ammonia emission factor of 226kt NH_3-N yr^{-1}. The largest contributors to this figure on an individual basis were dairy cattle, at 16.9g animal^{-1} day^{-1}. Beef cattle were allocated a much lower emission factor at 4.7g animal^{-1} day^{-1}.

Water use is also under considerable pressure from the livestock sector (Steinfield et al., 2006). Agriculture accounts for around 92% of humanity's global freshwater footprint (Gerbens-Leenes et al., 2013); around a third of this is associated with livestock products, and production of beef has been shown to be particularly costly in this respect (Hoekstra & Chapagain, 2006; Eshel et al., 2014). As much of this footprint is associated with feed crop irrigation, the poor feed conversion rates of cattle is a contributing factor in this area. This is of lower relevance to the UK beef industry than that of more water-scarce nations; nonetheless, Chapagain & Orr (2008) calculated a production water usage of 5,432 Mm^3 yr^{-1} for the UK beef industry. This figure comprises 29% of water requirements for the livestock sector; with dairy production included, the total requirements make up 65% of UK livestock sector water usage.

Alongside water usage, of increasing concern is water pollution; nutrient runoff, often associated with application of artificial fertiliser or manure, is a leading cause of eutrophication of marine and aquatic ecosystems, causing losses of biodiversity and ecosystem services (Mason, 2002; Steinfield et al., 2006; Niemann et al., 2011). The EU Nitrates Directive (OJEC, 1991) is one example of recognition of this issue in policy. Of additional concern are other impacts to water courses, including increased runoff (from soil compaction and deforestation), reduced infiltration and degradation of watercourse banks (Steinfield et al., 2006).

Biodiversity is also impacted by agricultural production, with livestock and arable production likely to be among the leading causes of the current high rates of species extinction and biodiversity loss (Steinfield et al., 2006). In the context of the UK livestock sector, Sutherland et al. (2007) suggest that modifications to current livestock grazing strategies will be necessary in order to maintain biodiversity. However, livestock farming may be less damaging in this respect than equivalent arable production; the latter also requires significant management intervention (e.g. Meek et al., 2002) in order to prevent adverse biodiversity impacts.

1.2.5. The IPCC (2006) guidelines and the tier system

The IPCC (2006) guidelines for national GHG reporting provide a reference methodology and decision support tool to standardise the derivation of national-level GHG emissions inventories. The 2006 guidelines integrate and expand upon an original set of guidelines published a decade previously (IPCC, 1996). In addition to their intended use in national-level inventories, they also form the basis for many assessments of smaller scope or scale (e.g. Beauchemin et al., 2010; Hillier et al., 2011; Cardoso et al., 2016).

The IPCC (2006) guidelines utilise a three-tier system to categorise the depth of assessment of an emission source. These are published together with 'good practice' guidelines to support the decision as to the choice of tier for a particular emissions source. Moving to a higher tier generally improves accuracy and reduces uncertainty, but requires more detailed inputs. While some general methods are applicable for each tier, ascending tiers become more situation-specific and hence require tailored methodologies. When conducting a calculation based on IPCC tiered methodology, various tiers can validly be employed as deemed appropriate; i.e. if data is available to conduct a Tier 2 assessment in one area, then this can be done alongside Tier 1 assessments in other, data-deficient areas.

Tier 1 methods are designed to be the simplest to use and contain the highest proportion of generic methodology and parameter values. Whilst country-specific data are needed, globally available, low-resolution data is generally sufficient accurate to the level required by this methodology. Tier 2 assessments follow the same basic methodology as those employed by Tier 1, though employ country- or region-specific data in place of generic emission factors and spatially coarse activity data. Often a mix is necessary, but Tier 2 methodology should seek to utilise higher-resolution data for the majority of livestock or land-use categories.

Tier three assessments involve considerably higher order methodologies, and as such are designed to describe the underlying processes to high levels of detail. These are not standardised as in lower tiers, but should be determined according to the required application. The IPCC (2006) provides good practice guidelines to standardise development of these methods, including prescription of quality checks, audits and validations. Datasets will account for high levels of environmental detail, such as soil type, age, management activities, land use change over time and so on. If livestock are included in the assessment then there will be detailed levels of data disaggregation on the basis of factors such as species, breed, body weight, age and so on (Dong et al., 2006).

The IPCC (2006) provide detailed guidelines for choosing the methodology tier. Choice is broadly based upon data availability and requirement for accuracy. The latter is in turn based upon the significance of the LCA category or sub-category to be assessed (Dong et al., 2006). In line with the tier system, the IPCC (2006) details methodologies for calculating emissions from a range of biological, industrial and agricultural processes. These form the backbone of many whole-farm and LCA calculators (see chapter two), and as such, it is worth giving a brief overview of these methodologies. Sections 2.3 – 2.6 consider these methodologies and their application in the process of agricultural carbon footprinting.

1.2.5.1. Emissions from livestock and manure management

The IPCC (2006) guidelines concerning direct livestock emissions are concerned entirely with CH_4 and N_2O. Net CO_2 emissions from livestock are assumed to be zero; the CO_2 assimilated by plants is consumed by the animal and returned to the atmosphere as respired CO_2. The IPCC (2006) standardised methodology for calculation of these emissions requires, at minimum, definitions of livestock subcategories, annual populations and, for higher tier calculations, feed intake and characterisation. Direct livestock emissions are sorted into three categories (Dong et al., 2006) a) CH_4 emissions from enteric fermentation, b) CH_4 emissions from manure management, and c) N_2O emissions from manure management.

1.2.5.2. Emissions from managed soils

The IPCC (2006) methodology considers both direct and indirect N_2O emissions from managed soils. Direct emissions can be viewed as those which occur directly from the land in question; indirect emissions are those caused by management practices on the land in question, but which ultimately occur from other areas. Indirect emissions are possible largely due to leaching, runoff and volatilisation and deposition of N_2O 'precursors', processes which serve to remove the source of N_2O emission from the geographical location of the land in question.

For direct emissions, the following sources are considered:

a) Synthetically produced nitrogen fertilisers. Note that this methodology includes only N_2O emitted as a result of fertiliser application; considerable CO_2 is released during the fertiliser production process. This is accounted for separately as embedded emissions.

b) Organic nitrogen applied as fertiliser. Consideration of this emission source must take place in the context of manure management emissions (section 2.4); care must be taken that the methodologies do not overlap.
c) Nitrogen returned to the soil in the form of crop residues, i.e. remaining organic material following crop harvest.
d) Urine and dung deposited on managed soils by grazing animals. Likewise, this must be calculated in consideration of manure management emissions (section 2.4).
e) Nitrogen mineralisation associated with loss of soil organic matter (SOM). This can result from land use change (LUC) or management of mineral soils.
f) Drainage/management of organic soils.

Two pathways for indirect emissions from managed soils are identified by the IPCC (2006). Firstly, volatilisation of NH_3 and NO_x, and deposition of these gases, and their products NH_4^+ and NO_3^-, onto soils and surface water can contribute to N_2O release in an analogous way to directly applied NH_3/NO_x fertiliser. A second pathway is formed by leaching and runoff of NO_3^- and NH_4^+ from synthetic and organic fertilisers, crop residues, and mineralisation of soil nitrogen caused by changes in land management. These substances may bypass biological retention mechanisms where there is sufficient water flow, or where they exist in the soil in excess of biological demand. Nitrification and denitrification processes then produce N_2O in the groundwater below the soil, in riparian zones receiving runoff, or in streams, rivers and estuaries which are contributed to by this runoff. The following sources of indirect N_2O emissions are considered in the IPCC (2006) methodology:

a) Synthetic nitrogen fertilisers.
b) Organic nitrogen fertilisers (manure, compost, sewage etc.).
c) Above- and below-ground crop residue nitrogen.
d) Nitrogen mineralisation associated with a loss of SOM.

1.2.6. Emission metrics used in greenhouse gas reporting

Global Warming Potential (GWP) is the current metric used to normalise the impacts of emissions of different GHGs under the UNFCCC (Reisinger et al., 2011). The first GWP metrics were produced by the IPCC (1995) as part of the Second Assessment Report. Whilst others (such as GTP) have since been proposed, GWP remains the popular choice of policymakers (Manning & Reisinger, 2011), and is therefore the emission metric discussed in this section. Global Warming Potential is a physical metric derived from the lifetimes and radiative forcing values of GHGs (IPCC, 2013) relative to those of CO_2; as such, there exist a variety of areas for uncertainty in the production of this metric. These include uncertainties in the radiative efficiency and lifetime of the GHG, together with background concentrations. Where the gas in question is not CO_2, describing GWP in terms of CO_2 equivalents (CO_2-eq) also incorporates those uncertainties associated with the Absolute Global Warming Potential (AGWP) of CO_2, the reference gas for the GWP metric.

Manning & Reisinger (2011) show that, aside from the issues of standardising to the CO_2 AGWP, the uncertainties associated with GWP for any gas come from three different factors; the radiative forcing caused by emission of the GHG, the rate at which a concentration caused by a pulse emission declines with time, and the indirect effects of that emission on other GHGs within the atmosphere. The AGWP for CO_2 is a major factor in contributing to uncertainties in GWP for all GHGs (Manning & Reisinger, 2011). This metric has come under considerable scrutiny as understanding of the global carbon cycle has progressed, and as such reported values for the AGWP of CO_2 have changed considerably since the IPCC Fourth Assessment Report (IPCC, 2007).

A balance of sorts exists between oceanic and atmospheric CO_2 (Caldeira & Kasting, 1993; Reisinger et al., 2011). As both bodies become saturated, the radiative efficiency of added atmospheric CO_2 decreases, whilst the proportion of CO_2 diverted from the atmosphere by absorption into the CO_2-saturated upper ocean decreases, increasing the proportion of emissions which enter the atmosphere. This acts to slow the decrease in CO_2 AGWP which could be expected with increasing concentrations. Nevertheless, Reisinger et al. (2011) concluded that a large proportion of the uncertainties associated with this metric stem from uncertainties in future CO_2 emissions; while a best-estimate concentration pathway (RCP3) results in only 2% decrease in the $AGWP_{100}$ for CO_2 by 2100, the highest (RCP8.5) sees a 36% decrease in the same metric.

Contributing to the Fifth Assessment Report (IPCC, 2013), Joos et al. (2013) produced a comparison of carbon cycle-climate models, and found that in modelling a 100 Gt-C pulse emission of CO_2 over a 1000 year time horizon, variations in results from the models suggested that 25 Gt-C ± 9% remained in the atmosphere. Together with an assumed ±10% uncertainty in radiative efficiency, this resulted in an AGWP for CO_2 with uncertainties of ±18% at a 20-year time horizon and ±26% at the commonly used 100-year time horizon.

Uncertainties in the ongoing AGWP for CO_2 have considerable implications for calculating the GWP for other gases, a metric which is normalised to the AGWP for CO_2. Incorporating this into the calculation of uncertainty in the GWPs for CH_4 and N_2O, Reisinger et al. (2011) estimated, for both gases, an uncertainty of −15/+20 for the GWP_{20} and −20 to +30% for the GWP_{100}. The calculations did not take into account uncertainties in the AGWP for CH_4 or N_2O.

Boucher (2012) estimated a ±20% uncertainty for the GWP_{100} of methane. The methods of this study differed from those of Reisinger et al. (2011) in that the result was calculated using Monte Carlo analysis of uncertainties in perturbation lifetime and radiative efficiency, Boucher (2012) assumed a constant background atmosphere following the modelled emissions pulse, as in Reisinger et al. (2011).

Assessing and combining the results of these studies, the IPCC (2013) estimates an uncertainty of ±30% for CH_4 GWP_{20}, and ±40% for CH_4 GWP_{100}. This uncertainty is dominated by the uncertainties in AGWP for CO_2, and by the indirect effects of CH_4

emission. For longer lived gases, including N_2O, the IPCC (2013) provide a GWP uncertainty estimate of ±20% for the GWP_{20} and ±30% for the GWP_{100}.

1.3. Farm-level greenhouse gas tools: introduction and review

This section aims firstly to review the role and approaches of existing farm-level GHG footprinting tools in the context of mitigation of agricultural emissions, in order to gain insight into their rational, scope and methods, and to provide a basis for critique of the current approaches. This will enable the development and definition of the aims, objectives and research and development priorities of this thesis.

A farm-level GHG footprinting tool is defined for the purposes of this review as an empirical, broad-scope tool designed for the purpose of providing better understanding of GHG emissions from a farming enterprise.

1.3.1. AgRE Calc tool

The AgRE Calc was provided to the author at the beginning of this project with the aim that development and utilisation of the tool would form the basis for this research thesis. A large proportion of the *raison d'être* of this project was therefore to develop the AgRE Calc tool to improve its applicability to the challenges defined in section 1.2.2. As such, the state of development of the model changed considerably throughout the thesis (the majority of these developments are described in chapter three), and the tool is reviewed in this section as it was provided to the author at the beginning of this thesis (01/09/2014).

AgRE Calc (SRUC, 2014), standing for Agricultural Resource Efficiency Calculator, was developed by the Consulting Division of Scotland's Rural College. Development of the tool took place in the context of the Scottish Government's Farming for a Better Climate initiative. The calculator was developed initially in Microsoft Excel, though is available to the public in web-based form only[1]. The model is used extensively as a consulting tool, and provides a series of key performance indicators alongside GHG emissions estimates. While it forms a major part of SAC Consultancy Services, the model is nevertheless available free regardless of affiliation with this organisation. The tool was developed in line with IPCC (2006) Tier 1 and two methodology, and is PAS2050 certified.

IPCC (2006) Tier 2 calculations are employed to calculate livestock and manure management emissions; this level of detail is rare amongst sampled carbon calculators and requires detailed data input in this section. Fertiliser embedded emissions are calculated using Carbon Trust (2010) emission factors, whilst soil emissions from fertiliser application and from crop residues follow IPCC (2006) Tier 1 methodology.

[1] http://www.agrecalc.com/

System boundaries include embedded emissions for material usage (e.g. plastics) and for imported feed; these are sourced from Footprint Expert v3.1 (Carbon Trust, 2010).

Electricity, renewable energy and fossil fuel emissions are calculated using emission factors from the DEFRA/DECC (2011) Conversion Factors for Company Reporting. Finally, carbon sequestration from woodland is included in the system boundaries, and estimates follow IPCC (2006) methodology. Though not yet available in the online version of the model, SRUC is undertaking work to extend the system boundaries of the model to include a post-farm gate emissions estimate, and to include other environmental impacts such as land use change and eutrophication in the calculations.

Results are presented in a breakdown detailing separate emission types and sources. The system also allows direct pairwise comparison to separate reports, meaning hypothetical or annual changes can be assessed.

1.3.2. Farm (CFF) Carbon Calculator

The Climate Friendly Food Carbon Calculator (CFF, 2012) is an online tool funded with the support of NESTA. It places a strong emphasis on organic agriculture and horticulture. The model is based on Tier 1 methodology (IPCC, 2006), and follows a whole farm approach. The calculator is JavaScript based and available on the web[2].

The model has the capability to assess GHG emissions from fuel and electricity use, material consumption (e.g. plastics), crop production (including embedded emissions in imported feeds), fertiliser use, direct livestock emissions and manure management. There is also a strong emphasis on new-start or expanding enterprises, with the facility to assess emissions associated with building materials and capital items such as farm machinery. Lastly, there is a function to assess post farm gate haulage costs (in terms of additional fuel use) and waste.

Aside from consideration of inputs, the model also provides an assessment of carbon sequestration. Sequestration potential is assessed for on farm ‘wild’ areas such as field margins, hedges, wetlands and woodlands. The model also has the capability to assess managed land such as orchards and vineyards. The Farm Carbon Calculator does not directly assess grazed or managed grassland, but does have the capability to assess the carbon sequestration by soil based on annual soil organic matter (SOM) change, if this data is input by the user. In the results, this sequestration potential is offset against on farm emissions.

The model system boundaries are limited in that very little emphasis is placed upon N_2O emissions. Where these are associated with crop residues, they are considered in the model; however, the calculations take no account of N_2O emissions from fertiliser spread or from manure. Fertiliser is accounted for in terms of embedded emissions only; likewise, manure is accounted for only in terms of CH_4 emission. The authors state that

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[2] http://www.coolfarmtool.org/

this omission is due to the significant variation in these emissions caused by different climatic and soil conditions, and that collecting and inputting this data would be too onerous for users (CFF Carbon Calculator, 2012).

Colomb et al. (2012) reviewed the tool, and assessed it in comparison with others for skill and time requirements to complete a study. The authors used a scale of 1−4, with 1 representing the minimum skill and time requirements. The CFF tool was assessed as level two for time requirement and as level three for skill requirements. Whittaker et al. (2013) also produced a multi-criteria analysis which included the CFF tool; in this, the calculator scored highly for user-friendliness and information provision, though less well in the transparency and comprehensiveness criteria.

In particular, Whittaker et al. (2013) found the developers' methodological approach to be relatively opaque; supporting this conclusion, this review process identified a reference list published by the developers, but with little indication as to where or how the published sources were applied in the development of the tool.

1.3.3. CPLANv0 tool

CPLANv0 (SEE360, 2007) is a free to use carbon calculator set up by tenant farmers based in central Scotland. The development was supported by public funding provided by the South Lanarkshire "LEADER +" grant. The model forms a key component of the agricultural consultancy business SEE360 Ltd.

CPLANv0 is complemented by CPLANv2, a more detailed calculator with a charge of £29.99 per calculation performed. CPLANv2 was excluded from this review due to the access restrictions this charge imposes. Both models are based on IPCC (2006) methodology, and follow a whole farm approach including carbon sequestration. CPLANv0 is web-based[3] and uses JavaScript to perform calculations. Other than the statement that IPCC (2006) methodology has been observed, there is little detail given as to the specific calculations performed by the calculator.

The model methodology is therefore relatively opaque; this assessment is reflected by Whittaker et al. (2013), who awarded the model a transparency score of 17% (average = 49%). The system boundaries include CH_4 from enteric and manure sources, though exclude N_2O from manure or fertiliser spread. Nitrous oxide from crop residues is assessed. Embedded emissions from imported fertilisers, including organic fertilisers, are included, as are those associated with fossil fuel and electricity use. Renewable energy use is not considered. The sequestration potential of standing woodland is assessed, as well as impacts from forestry and land use change. The model assesses a total of 57 sub-categories, with the heaviest focus on sequestration and land use change.

[3] http://www2.cplan.org/

1.3.4. CALM tool

The CALM Carbon Calculator was developed by the Country Land and Business Association, in partnership with Savills (CLA, 2009). Funding was supplied by the East of England Development Agency and the Crown Estates, with later updates sponsored by Natural England. The tool is available online.[4]

The model methodology is described as following the most recent National Inventory Report (published by the National Atmospheric Emissions Inventory), though appears to have been most recently updated in 2009. With no specific source cited for calculations, it is difficult to ascertain the provenance of model methodology.

Amani & Schiefer (2011) found that the CLA (2009) made some adjustments to the National Inventory Report methodology to allow the calculator to be applicable on a farm level. The most significant change involved the re-apportioning of manure emissions. These include only the emissions from manure used or brought onto the farm. In this respect, embedded emissions for manure brought onto the farm are assessed (these are often neglected by other models), while emissions for manure produced on farm but exported are neglected.

Despite this lack of transparency, the model has reasonably comprehensive system boundaries. The methodology assesses N_2O emissions from crop residues, fertiliser spread and manure management, within the bounds described by Amani & Schiefer (2011). Enteric CH_4 emissions and those from manure management are considered, as are emissions associated with on-farm fuel and electricity use, including a variety of renewables. A variety of contracting activities are also included. The model has the capacity to assess emissions and sequestration associated with forestry, soil organic carbon and land use change.

Notable system boundary omissions are embedded emissions associated with imported livestock feed and bedding. The system boundary ends at the farm gate, and does not account for transport off-farm or emissions associated with product distribution.

Harper Adams University College (2011) conducted a review of the CALM Calculator, and concluded that the tool produced markedly different results to a by-hand calculation using IPCC (2006) methodology. In particular it was noted that calculations of CO_2 emissions were markedly (84%) higher than the by-hand result. The authors also noted that it was difficult to ascertain the cause of the discrepancy due to a lack of transparency in the methods employed by the CALM calculator.

In contrast with these impressions, Whittaker et al. (2013) scored the CALM tool relatively highly (75%) for transparency as part of a multi-criteria analysis. However, the rationale behind this result is not clear; several scores on this section of the MCA appear at odds with the experiences of other users of the tool.

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[4] https://www.cla.org.uk/advice/what-cla-calm-calculator/

Whittaker et al. (2013) rated the tool highly (83%) in the informative category; this backs up experiences of the tool gleaned from this review. The CALM Calculator produces reports in a variety of formats, including .pdf and .csv files. The reports contain a thorough, section-by-section breakdown of the output into separate GHGs, improving the relative traceability of the results.

1.3.5. FCAT Calculator

The Farm Carbon Assessment Tool (FCAT) is a free online[5] self-assessment tool developed and provided by the Soil Association as part of the EU Low Carbon Farming Project (Soil Association, 2013). The tool focuses heavily on soil management and inputs, though includes facility for livestock data input.

Aside from an assessment of farm emissions from energy usage, the tool provides its report in the form of a series of performance indicator scores (given in arbitrary units, 1−5). This is a relatively opaque methodology, and there is little information available on how these scores are calculated. Provision of results in this form severely limits comparison with other calculators; aside from the energy usage emissions, no further comparison was made in this review.

1.3.6. Cool Farm Tool

The Cool Farm Tool (Hillier et al., 2011) was developed at the University of Aberdeen as a mid-level calculator designed to cover a range of farming practices. It was originally engineered in Microsoft Excel, and is now freely available under a creative commons licence as a web-based application.[6] Hillier et al. (2011) state that the tool was designed to function at an intermediate level. Requirement for the high levels of data input of process-based models such as DAYCENT (Del Grosso et al., 2006) was avoided, but provision for data input beyond the standard Tier 1 inventory methods (Dong et al., 2006) were included so as to provide useful insight on a local scale.

Hillier et al. (2011) made use of a variety of emission factor databases and sub-models to provide farm-level functionality for Cool Farm Tool. Firstly, the Ecoinvent emission factor inventory (Ecoinvent Centre, 2007) was used to provide emission factors for fertiliser production and renewable electricity usage. Hillier et al. (2011) also incorporated a sub-model developed by Bouwman et al. (2002) to determine N_2O emissions relating to fertiliser usage; this model is based upon a global dataset of over 800 sites. IPCC (2006) methodology was used for livestock and manure management calculations. The model is stated to contain provision for Tier 1 or Tier 2 level calculations, as allowed by input data (Hillier et al., 2011).

Ogle et al. (2005) conducted a meta-analysis which quantified the impacts of agricultural land management on organic carbon content of a variety of soil types. The results of this study were incorporated into the Cool Farm Tool by Hillier et al. (2011), enabling

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[5] Tool appears to have been discontinued as of 10/2018.
[6] http://www.coolfarmtool.org/

assessment of the impacts of management change by the model. Defined management practices included input application levels and tillage practices; coefficients were provided for four soil types (two of which are relevant to UK agriculture) changing between three levels of each practice. A separate set of coefficients, derived from a long-term study by Smith et al. (1997), allow for separate consideration of organic manure application and the effect of this practice on soil organic carbon (SOC).

The Cool Farm Tool is intended for application worldwide, and so has provision for global variability in the inputs (Hillier et al., 2011). These include consideration of tropical soils in the incorporated dataset from Ogle et al. (2005), and inclusion of a database from GHG Protocol (2003) which provides CO_2 emission factors for grid electricity by country.

1.3.7. Carbon Calculator for New Zealand Agriculture and Horticulture

The Carbon Calculator for New Zealand Agriculture and Horticulture (AERU, 2008) was developed by the Agribusiness and Economics Research Unit (AERU) of the University of Lincoln, NZ, and is freely available online.[7]

The calculator provides the facility to assess emissions relating to farm energy and fuel use, including that of contractors. Methane and N_2O emissions relating to livestock and manure are assessed, though no differentiation between manure storage strategies is apparent. Embedded emissions in fertiliser are considered, as are N_2O emissions related to application rate. There is no consideration of N_2O emissions relating to crop residues produced on farm; while the model does consider an embedded emission factor for imported feed, it is not clear where the system boundaries lie in this area. Carbon sequestration is not considered by the model.

The extent to which the model is specific to New Zealand is not clear; no indication is given as to the source of the methodology utilised in the model. The title suggests it is regionally specific. A search of the published literature did not reveal any case studies performed using the calculator. Colomb et al. (2012) produced a review which included the calculator, rating at the minimum level for time and skill requirements. The authors suggested that the tool is most suited to raising awareness of major agricultural GHG sources, rather than for specific footprinting, decision making, or performing GHG audits.

1.3.8. Farming Enterprise Greenhouse Gas Calculator

The Farming Enterprise Greenhouse Gas Calculator was developed at the University of Queensland to assess emissions from a variety of agricultural enterprises in this area. Limited published information was available on the tool, though it became clear during initial assessment of the tool that the methodology was specific to the Queensland area, with no option for user-defined inputs to expand the model capabilities beyond this point.

[7] https://www.carbonfarming.org.nz/calculators/

1.3.9. CCaLC Carbon Footprinting Tool

The CCaLC Carbon Footprinting Tool (CCaLC, 2014) was developed by the University of Manchester’s School of Chemical Engineering and Analytical Science. The tool differs from the majority of reviewed calculators in that the functional unit of output (in most cases whole farm annual emissions) is entirely user defined; the model is, in essence, a multi-purpose LCA calculator.

Thus, CCaLC can be used to footprint products and processes from a wide variety of industries. While this additional functionality represents potential for a wide range of applications, it also means that the tool is considerably more complex than many others; crucially, there is no guided, step-by-step approach to utilising the tool (as with others reviewed here), and system boundaries are entirely user-defined. This means gaining an accurate result is time-consuming and is likely to require training for most users. This problem is addressed with the provision of training courses by the developers of CCaLC.

The tool is Excel-based, with a free download available from the web.[8] Functionality is provided entirely by VBA scripts, with very limited user access to database calculations. The tool incorporates an extensive Ecoinvent LCA database from which it derives a great deal of functionality. Because of the wide application potential of the CCalC tool, and lack of specificity to the livestock sector, this tool was excluded from further review.

1.3.10. Muntons Carbon Calculator

Muntons PLC is an international company specialising exclusively in the production and supply of malts to the food and drinks industry. Initial assessment served to identify that this model is specifically designed provide assessments within this sector, and thus the system boundaries are confined entirely to assessment of cereal yield, diesel consumption, seeds and pesticides (Whittaker et al., 2013), making it incompatible with wider agricultural practice, particularly in the area of livestock production.

1.3.11. Summary of reviewed farm-level tools

Table 1.1 provides a summary and breakdown of the major attributes, methodological approaches and system boundaries of the tools included in this review.

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[8] http://www.ccalc.org.uk/

Table 1.1. Summary of attributes for tools reviewed in sections 1.3.1 – 1.3.10.

		Emissions sources/sinks								Methodology		
Model Name	**Organisation**	**CO_2 from energy use**	**Enteric CH_4**	**CH_4 from manure**	**N_2O from fertiliser**	**N_2O from manure**	**N_2O from residues**	**Post-farm gate**	**Carbon sequestration**	**IPCC Tier 2 (livestock)**	**Non-GHG impacts**	**Uncertainty estimate**
AgRE Calc	SRUC	Y	Y	Y	Y	Y	Y	N	Y	Y	N	N
CFF Calculator	Farm Carbon Calculator	Y	Y	Y	Y	Y	N	Y	Y	N	N	N
CPLANv0 Calculator	SEE360 Ltd	Y	Y	Y	Y	Y	Y	N	Y	N	N	N
CALM Calculator	Country Land and Business Association	Y	Y	Y	Y	Y	Y	N	Y	N	N	N
FCAT	The Soil Association	Y	N	N	N	N	N	N	N	N	Y	N
Cool Farm Tool	Cool Farm Alliance	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	N
Calculator for NZ Agriculture	Lincoln University, NZ	Y	Y	Y	Y	Y	N	N	N	N	N	N
Farming Enterprise GHG Calc.	University of Queensland	ǂ	Y	?	Y	?	Y	N	N	N	N	N
CCalC	University of Manchester	Y	Y	Y	N	N	N	Y	N	N	Y	N
Muntons	Muntons PLC	ǂ	N	N	Y	N	N	Y	N	N	N	N

ǂ = fossil fuel emissions only ? = data unavailable

The tools reviewed in sections 1.3.1 – 1.3.10 are relatively heterogeneous in origin, design and approach. Nevertheless, some commonalities were present, and these are worth discussing. Almost all tools chose to include direct and indirect emissions from livestock in the scope, reflecting the magnitude and perceived importance of this source. Those which did not include this emissions source were designed specifically for non-livestock enterprises. Inclusion of nitrous oxide from managed soils was relatively universal, though some tools (e.g. CFF, 2012) differed slightly in the specific sources they included. Inclusion of emission from energy use on farm was also an almost universal choice; whilst energy use in livestock production forms a relatively small proportion of the footprint (Opio et al., 2013), its inclusion here may reflect its relative simplicity of calculation and prominent inclusion in GHG accounting methodologies (e.g. GHG Protocol, 2012; DEFRA/DECC, 2015). Interestingly, though the efficacy of forestry in offsetting emissions is the subject of ongoing discussion (Cannell, 1999), the majority of tools appeared to include this as a carbon sink.

Del Grosso et al. (2006) suggested that IPCC tier 1 level methodologies may not be sufficiently precise to give useful insight at farm level. This conclusion appears to have been echoed by some tool developers (e.g. Hillier et al., 2011) in addition to AgRE Calc, but the majority of tools appeared to follow this simplified approach. Uncertainty assessment, identified in the literature as being of considerable potential importance in GHG footprinting (Gibbons et al., 2006; Röös & Nylinder, 2013), was not incorporated by any tools. The reason for this is not clear – some developers acknowledge its relative importance (CFF, 2012) – but may be related to the computational demand this calculation is likely to impose. Several tools incorporated estimates of non-GHG environmental impacts, though the methods by which these were calculated were not always clear.

One notable point which became apparent when researching the tools was the considerable inconsistency of methodological documentation, leading to a lack of transparency in the modelling approaches used. Some developers (e.g. Hillier et al., 2011) thoroughly document the model methodology for users, while others e.g. CPLANv0 (SEE360, 2007) provide little or no supporting documentation. With the notable exception of the Cool Farm Tool, the majority of tool development appeared to have taken place outside of the peer-review system.

1.4. Thesis aims and objectives: Development of the AgRE Calc farm-level greenhouse gas modelling tool

1.4.1. Scope of assessment: modelling environmental impacts in AgRE Calc

A fundamental principle of LCA is to provide a comprehensive basis for environmental assessment (Finkbeiner, 2009; Röös et al., 2013). AgRE Calc was designed originally as a carbon footprinting tool (SRUC, 2014), though has potential to expand its scope of assessment to include other impacts. The consideration of one impact (global warming potential) to the exclusion of all else to some extent violates this LCA principle, and so it is important to consider the implications of this in relation to development of the AgRE Calc model.

Climate change, in comparison to the other impacts discussed above, has received considerable attention in the global environmental agenda (Röös et al., 2013). This means that the commonly used global warming potential (GWP) metric, whilst not beyond critique (e.g. Smith, 2003; Shine, 2009), is generally well accepted. Greenhouse gas emissions are also relatively unique in being almost entirely non-spatially specific; emissions of climate-forcing gases diffuse quickly and cause similar impacts regardless of the precise point of origin (Röös et al., 2013). By contrast, impacts such as eutrophication and acidification are much more spatially specific (Posch et al., 2008; Röös et al., 2013), and real-world impacts can vary over small geographic scales. Where a farm-level tool or LCA modelling approach is not spatially specific in this sense, characterisation of these factors may be problematic.

Whilst there exist generally accepted metrics for impacts such as eutrophication and acidification (PO_4^{3-}-eq and SO_2-eq respectively; Williams et al., 2006), others are harder to quantify. Toxicity, for example, is an important environmental impact, but heterogeneity in accounting methods has been cited as a reason for its exclusion from previous assessments (Pant et al., 2004). Biodiversity, also, is not an inherently quantifiable concept, and selection of an appropriate metric can be a challenging problem even for specifically defined studies and assessments (Gotelli & Colwell, 2001). Penman et al. (2010) considered the adaptation of a methodology for accounting for biodiversity in LCA, but concluded that considerable research and development would have to be conducted in order to render it feasible in the foreseeable future. Key issues in this respect were those of small-scale landscape heterogeneity, meaning practices could have different impacts across small geographic scales, and definition of a baseline biodiversity state in order to separate the process of interest to the LCA from previous changes or disturbances.

Providing a perspective specific to the livestock sector, Röös et al. (2013) conducted a meta-analysis which analysed a number of environmental impacts (primary energy use, land use, acidification potential, eutrophication potential, and pesticide use) alongside a measurement of global warming potential for livestock production systems. The authors found that in general, GHG emissions showed a strong positive correlation with many other environmental impacts, and concluded that the omission of additional environmental impacts from an LCA assessment was unlikely to lead to false economies in GHG mitigation, e.g. reducing GHG emissions while increasing eutrophication impacts. The authors also found that a key reason for this was that many impacts (e.g. eutrophication, acidification) have similar precursors to GHG emissions (namely NH_3 and NO_x); following this, the development of methodologies to account for these impacts relies to a large extent on a common base methodology (e.g. Williams et al., 2006).

In summary, modelling the majority of non-GHG impacts represents a considerable challenge, which stems largely from the difficulties associated with quantifying these impacts. Accurately and precisely accounting for impacts which are highly variable over small geographical scales (such as eutrophication, acidification and biodiversity) is a particular challenge, and may be relatively incompatible with the concept of a non-spatially explicit model such as AgRE Calc. This is compounded by the small scale for which the model is designed; while non-spatially specific assays exist for non-GHG impacts (e.g. Williams et al., 2006; Nguyen et al., 2013), these tend to be large-scale, where the effects of small-scale regional heterogeneity will largely be smoothed out. Added to this, Röös et al. (2013) demonstrated that the risk of jeopardising other impact categories through focusing on GWP is relatively slight in the case of livestock production systems.

For these reasons, and those of tractability, the development strategy defined for the AgRE Calc model over the course of this thesis will focus solely on improving the model's ability to account for GHG emissions from agriculture. As noted, the base methodology for many important non-GHG impacts is the same, and so a focus on GHG emissions at this stage does not necessarily preclude the development of non-GHG calculation processes at a later date.

1.4.2. Increasing the transparency of extant farm-level greenhouse gas modelling tools

Section 1.3 identified that the majority of extant farm-level tools do not effectively account for their methodological choices, either in the peer-reviewed or grey literature. Nonetheless, almost all tools draw on peer-reviewed approaches in one form or another. These tools are also sought and utilised by users of various types (Hall et al., 2010). The requirement for more information to be made available on these tools has been implicitly acknowledged by the multitude of reviews which have been carried out for these models (Colomb et al., 2012; Whittaker et al., 2013; Clift et al., 2014; Keller et al., 2014). However, these reviews have largely focused on a) qualitative approaches, and b) arable cropping (rather than livestock) enterprises. The former approach has been relatively limiting given the dearth of published information available to reviewers.

This thesis is aimed primarily towards the development of the AgRE Calc tool as an environmental calculator for the beef industry, but secondarily has a broader scope in that it seeks to further the role and efficacy of farm-level modelling approaches in general. Based on the above observations, it was identified that a gap in the literature exists for a thorough, quantitatively-based review of extant farm-level modelling approaches, focusing around livestock production. A primary objective of this thesis is therefore to follow this approach in order to build upon the knowledge acquired during the review carried out in section 1.3. This will serve to a) provide greater insight into the methodologies utilised by the developers of existing tools, and b) benchmark the AgRE Calc tool against existing tools in terms of methodology and results.

1.4.3. Improving the ability of AgRE Calc to model emissions associated with livestock rations

The diet of beef cattle plays a large role in the GHG emissions associated with production (Dong et al., 2006). Where the animals subsist on a poor-quality diet, performance is low, and a greater proportion of dietary energy is released as enteric methane. Improving rations ('intensification' of production) has the effect of increasing performance (e.g. increased growth rate and increased final live weight) and reducing enteric emissions; both of these factors serve to reduce emissions intensity. As such, a large proportion of studies focused on reducing the emission intensity of beef systems focus on dietary improvement as a mitigation strategy (e.g. Nguyen et al., 2012; Hünerberg et al., 2014; Cardoso et al., 2016).

However, there exists a trade-off associated with this approach; namely that higher-quality diets typically have higher emissions (largely composed of N_2O) associated with the production of the ration components (Hünerberg et al., 2014). Whilst some recent studies suggest that intensification of production systems is an efficient way to reduce net emissions (Pelletier et al., 2010; Cardoso et al., 2016), others draw a different conclusion (Subak, 1999; Casey & Holden, 2006). As an important trade-off, it is therefore crucial that models used to assess the efficiency of production systems to account accurately for both sides of the trade-off, and to ensure that the model processes are closely linked (e.g. Janzen et al., 2006).

In addition, the vast majority of production systems in both hemispheres rely to a large extent on grazing as a source of cattle nutrition; even for feedlot-based finishing systems, the cow-calf system which supplies finishing animals is typically grass-based (e.g. Pelletier et al., 2010). Beef production is also cited as an important way of producing human-edible protein from extensive grassland which otherwise has no value as a source of human nutrition (EBLEX, 2009). Grazed forage therefore plays a prominent role in the feed ration for the majority of production systems, and the carbon footprint of beef production is intrinsically linked to the grassland component of the system.

The AgRE Calc tool currently utilises an emission factor database (Carbon Trust, 2010) to account for embedded emissions from crop production where livestock feeds are produced off-farm. For on-farm produced feeds, emissions are calculated based on user-supplied input data. Either approach has the required flexibility and precision to adjust modelled emissions based on changes to the livestock ration. For the other side, Tier 2 level methodology (Dong et al., 2006) is employed to account for livestock enteric emissions. This approach has the capability to adjust modelled enteric emissions in relation to dietary quality, but the input data required for this purpose (digestibility of the ration, as a percentage of gross energy) is currently selected from a relatively small set of expert-estimated values. The value is selected based on a user-defined description of the production system (e.g. 'upland suckler herd'), making it a relatively broad estimate and specific to the United Kingdom. The precision and accuracy of the AgRE Calc tool could be improved accordingly if the modelled dietary digestibility was more closely linked to the ration. An aim of this thesis is therefore to a) assess the potential for improvement of this calculation stream, and conduct this development if possible, and to b) conduct an assessment of the impact of dietary digestibility on the emissions intensity of production utilising this level of precision.

1.4.4. Uncertainty analyses: Developing Monte Carlo functionality within AgRE Calc

None of the farm-level tools reviewed in section 1.3 incorporated any ability to assess uncertainty in modelled emissions, though the developers of some (e.g. Hillier et al., 2011; CFF, 2012) acknowledge that this may be significant in many footprints. Some LCA studies of cattle production systems (e.g. Gibbons et al., 2006; Lovett et al., 2008; Dudley et al., 2014; Zehetmeier et al., 2014) conduct uncertainty assessments, though it is not the norm. Uncertainty in the IPCC (2006) guidelines has been identified as potentially significant in the case of agricultural emissions (Karimi-Zindashty et al., 2012; Milne et al., 2014). A common justification for the incorporation of an uncertainty assessment is that it will improve confidence in results (e.g. Gibbons et al., 2006), and may help to overcome some of the shortcomings of simplistic empirical models. Confidence in the results of farm-level tools was identified in section 1.3 as a potentially important shortcoming; this conclusion is reflected by other reviewers of these tools (Hall et al., 2010). Röös & Nylinder (2013), in considering uncertainty analysis in LCA, identify a number of sources from which uncertainties in modelled results can arise; many of these sources are accounted for in farm-level tools. The authors suggest that stochastic modelling, (i.e. Monte Carlo simulation) is the most appropriate method to assess uncertainty propagation throughout a complex model.

A development objective of this thesis is, therefore, to investigate the feasibility of the incorporation of Monte Carlo functionality into the AgRE Calc model, and to undertake this process, should it prove viable. In addition, review of the extant literature has identified that there exists no thorough, first-principles sensitivity analysis of epistemic uncertainty in holistically modelled emissions from a northern-hemisphere suckler beef system. Such an assessment would provide valuable insight into the confidence which can be placed on the results of farm-level models, and would be possible using a Monte Carlo-enabled version of the AgRE Calc model.

1.4.5. Final summary: Thesis aims and objectives

Section 1.1 established the importance of beef production to agricultural emissions globally, and sections 1.2 – 1.3 explored the potential of farm-level modelling approaches in gaining an insight into this. Based on these observations, the overall aim of this thesis is therefore to develop the farm-level GHG calculator AgRE Calc to improve its ability to provide decision support for GHG mitigation in the United Kingdom beef production industry, with a view to rendering these improvements relevant to challenges faced by developing beef systems. This geographical scope was defined based on a) the existing scope of the AgRE Calc model, b) the availability of data and methodological approaches to parameterise the UK beef industry, and c) the role of developing nations in acting as leaders in the development of efficient production systems. The previous subsections (1.4.1 – 1.4.5) broadly defined areas within this aim for development and research relating to the application of the AgRE Calc model to these global challenges. Based on this, the specific research goals of this thesis are:

a) Conduct an empirical assessment of the performance of extant tools to provide greater insight into the questions of methodology and real-world performance raised in section 1.3.
b) Develop the model to enable it to accurately account for changes in enteric and manure emissions related to cattle diets, as identified in section 1.4.3.
c) Further to b), and based on the role of grazing in beef production (1.4.3), conduct research into the possibility of developing a modelling approach to assess the impact of grazed ration quality on emissions from beef production.
d) Conduct an LCA of beef production systems with a focus on dietary quality, to a) highlight areas of good model performance and/or areas for further development, b) inform a narrative on the role of input data in LCA/farm-level modelling and c) stand in its own right as a contribution to the literature on emissions intensity of beef production.
e) Conduct research into the feasibility of optimising the AgRE Calc model for Monte Carlo simulation and, assuming this is possible, conduct an assessment of the impacts of epistemic uncertainty in farm-level modelling approaches.

Chapter Two

A comparison of farm-level greenhouse gas calculators in their application on beef production systems

2.1. Declaration of publication

The contents of this chapter were published as an original research publication in vol. 64 of the Journal of Cleaner Production (as Sykes, A. J., Topp, C. F. E., Wilson, R. M., Reid, G., Rees, R. M. (2017) A comparison of farm-level greenhouse gas calculators in their application on beef production systems. *J. Cle. Pro.* 64(2017) 398−409. DOI: 10.1016/j.jclepro.2017.06.197). The author of this thesis was the first and corresponding author of this publication. The content of this publication (including figures and tables) are reproduced here as chapter two of this thesis. Figures and tables have been renumbered to fit the numbering system used in this thesis, though are otherwise unchanged.

This study was conducted in line with the rationale identified in section 1.4.5 of this thesis; to gain insight into the methodology of commonly used existing farm-level tools, using empirical methods to overcome the shortage of information available on these tools. The tools tested here represent a subset of those reviewed in introduction section 1.3. A secondary aim of this approach was to provide an opportunity for the empirical comparison of the AgRE Calc tool with others which have similar stated aims and scope, and for the presentation of the AgRE Calc tool in a peer-reviewed context.

2.2. Introduction and rationale

Agriculture in the UK was responsible for the emission of 48 Mt CO_2-eq in 2008, a contribution of 8% to national emissions (Comittee on Climate Change, 2010). Under the Climate Change Act 2008, the UK Government is committed to reducing national greenhouse gas (GHG) emissions to 20% of 1990 levels by 2050; UK agriculture is correspondingly required to achieve a 34% reduction by 2020 (Comittee on Climate Change, 2008). This commitment in the UK follows international climate commitments; the EU Roadmap recommends a reduction in European agricultural emissions of 36−37% for 2030, and 42−49% for 2050 (Domingo et al., 2014).

Moran et al. (2011) show that to achieve this target will require considerable mitigation effort within the agricultural sector. The livestock sector contributes substantially to agricultural emissions and hence is likely to come under considerable scrutiny. Quantifying and mitigating GHG emissions from livestock is therefore of considerable policy importance on both national and international scales. Whilst quantification of farm-level emissions is not straightforward, it is a crucial step towards cleaner agricultural production (Schils et al., 2007).

A number of tools, developed in a variety of contexts, are available to assist with this process (Colomb et al., 2012). By providing a quantitative assessment of farm-level emissions, these tools perform a crucial role in facilitating reduction in the environmental impact of production. Some, such as the Cool Farm Tool (Hillier et al., 2011) have been developed within the academic sector; others such as CPLANv0 (SEE360, 2007) have been developed by businesses for consultancy-oriented purposes. Others, such as the CALM tool (CLA, 2009) are developed by not-for-profit organisations.

Hall et al. (2010) reviewed three UK-specific farm GHG accounting tools with the aim of recommending a single tool for promotion by the Scottish Government. However, the authors found that a qualitative approach was insufficient to recommend a single tool for this purpose. A lack of consensus in GHG accounting methods, together with lack of available information on tools was a key reason for this conclusion.

Without this consensus in place, each tool employs a unique range of methodologies, and the scope of assessment varies. This may be the product of the context in which a tool was developed; Colomb et al. (2012) note that this factor is likely to affect the depth and scope of a tool. Furthermore, the requirement to combine methodologies, inherent in the nature of such broad-scope models, is likely to further exacerbate differences. Some methodologies, such as the IPCC (2006) Guidelines, were not specifically intended for farm-level calculations, and so the necessary adaptation of these may act as further basis for disparity. Whittaker et al. (2013) found that tool transparency is often insufficient to shed light on the decisions made whilst adapting these methodologies.

In order to gain further insight into these issues, several studies have included quantitative analyses of these tools. These studies test tools in the context of the cultivation of palm oil and sugar cane (Keller et al., 2014), wheat in the United Kingdom (Whittaker et al., 2013), and a variety of European cereal cultivation scenarios (Lewis et al., 2013). All highlight disparities between tools in terms of scope, boundaries, and results. However, whilst illuminating in many respects, these studies have been limited in that all concern only arable enterprises. Given the contribution of livestock to agricultural emissions (Moran et al., 2011), coupled with the relative complexity of livestock systems (Schils et al., 2007) and the recognised issues with many available tools, the requirement for an empirical assessment of these tools on representative livestock enterprises is increasingly apparent.

This study aims to provide a reference point for prospective tool users in selecting a tool for their purposes, and for developers in further improving the tools. Tools of this type have proven potential in facilitating environmentally efficient agricultural production (e.g. Hillier et al., 2011), but the evidenced methodological variation and lack of accompanying information for many tools (Whittaker et al., 2013) means that users require further insight in order to realise this potential. Such an assessment must follow a critical, quantitative approach in order to provide maximum insight, and this study seeks to fulfil that requirement through a quantitative comparison of tool estimates based on a representative range of UK livestock enterprises. The relevance of such an approach is heightened by the importance of livestock production in both agricultural and national-level GHG budgets. Robust conclusions are sought as to the consequences of existing differences in accounting methods on the final farm-level footprint, and on corresponding implications for users and policy makers.

2.3. Methodology

2.3.1. Calculator selection

Farm-level carbon accounting tools were selected for review based on pre-determined criteria, defined as follows:

Tools had to be GHG calculators applicable to the livestock industry and specific to the agricultural sector. Data constraints (section 2.3.2) meant that tools had to be, if not UK-specific, at least UK applicable. Additionally, it was determined that tools must be publicly available without cost, and must function at farm-level.

Tools were sourced via web searches and from previously completed reviews, specifically Colomb et al. (2012) and Whittaker et al. (2013). Five tools were identified as complying with the above criteria and were selected for review (Table 2.1). These are described below. No suitable tools were knowingly rejected from the sample. Table 2.2 provides a summary of tools' scope and system boundaries.

Table 2.1. Farm-level GHG accounting tools chosen for review.

Name	Developer	Type	Website
AgRE Calc	SAC Consulting	Online	http://www.agrecalc.com/
Cool Farm Tool	Cool Farm Alliance	Online/Excel download	http://www.coolfarmtool.org/
CALM	Country Land & Business Association (CLA)	Online	http://www.calm.cla.org.uk/
CPLANv0	See360 Ltd.	Online	http://www2.cplan.org.uk/

CFF Calculator	Climate Friendly Food	Online	http://www.cffcarboncalculator.org.uk/

2.3.1.1. AgRE Calc

AgRE Calc (SRUC, 2014), standing for Agricultural Resource Efficiency Calculator, was developed by the consulting division of Scotland's Rural College. The tool forms part of the organisation's consultancy services, though is freely available for non-commercial use.

IPCC (2006) Tier II calculations are employed to calculate livestock and manure management emissions. Emissions from production of fertilisers and pesticides ('embedded' emissions) are calculated using Carbon Trust (2010) emission factors, whilst N_2O emissions from fertiliser and crop residues follow IPCC (2006) Tier I methodology. The tool also calculates embedded emissions for imported feed and bedding, based on emission factors (EFs) from FeedPrint (2012).

Electricity, renewable energy and fossil fuel emissions are calculated using emission factors from DEFRA/DECC (2011) Conversion Factors for Company Reporting. Finally, carbon sequestration from woodland is calculated using IPCC (2006) methodology at Tier I level. The online tool is certified under the PAS2050:2011 specification for GHG life cycle assessment (LCA) (BSI, 2011).

2.3.1.2. The Cool Farm Tool

The Cool Farm Tool (Hillier et al., 2011) was developed at the University of Aberdeen and is freely available under a creative commons licence. Hillier et al. (2011) state that the tool was designed to function at an intermediate level; requirement for high levels of data input was avoided, but provision for data input beyond the standard Tier I inventory methods (IPCC 2006) were included, providing insight on a local scale. The tool is unique in this sample in that the methodology has been published in peer-reviewed literature (Hillier et al., 2011) where the development of the Cool Farm Tool is described. The EcoInvent emission factor inventory (Ecoinvent Centre, 2007) was used to provide EFs for fertiliser production and renewable electricity usage. Hillier et al. (2011) incorporated a model developed by Bouwman et al. (2002) to determine N_2O emissions relating to fertiliser usage. IPCC (2006) methodology was used for livestock and manure emissions. Hillier et al. (2011) state that the model can perform Tier I or Tier II level calculations, as allowed by input data. The tool is not PAS2050 certified, though has been extensively reviewed in academic and non-academic literature.

2.3.1.3. The CALM Calculator

The CALM Carbon Calculator was developed by the Country Land and Business Association, in partnership with Savills (CLA 2009). The model methodology is described as following that used in the most recent National Inventory Report.

Model methodology assesses N_2O emissions from crop residues, fertiliser and manure management. Methane emissions from enteric fermentation and manure management are calculated. Embedded emissions from synthetic fertiliser and lime are assessed, as are emissions associated with on-farm fuel and electricity use. The model can also assess sequestration from forestry, soil organic carbon and land use change. Embedded emissions associated with purchased feed and bedding are not assessed. The tool appears to draw on methodology from the IPCC Guidelines for emissions from livestock and manure (Dong et al., 2006) and land management (de Klein et al., 2006), and the UK GHG inventory (DEFRA/DECC, 2013), though is not PAS2050 certified.

2.3.1.4. CPLANv0 Calculator

CPLANv0 (SEE360 2007) is a free-to-use carbon calculator which forms part of a consultancy business. The development was supported by public funding provided by the South Lanarkshire “LEADER +” grant. The model forms a key component of the agricultural consultancy business SEE360 Ltd.

CPLANv0 forms the basis for CPLANv2, a more detailed calculator which is not free to use. Other than the statement that IPCC (2006) methodology has been observed, there is little detail given as to the methodology of the CPLANv0 calculator. The system boundaries include CH_4 from enteric fermentation and manure. Nitrous oxide from crop residues and fertiliser is assessed. Emissions from fossil fuel and electricity use are also included. The sequestration potential of standing woodland is assessed, as well as impacts from forestry and land use change. The tool is not PAS2050 certified.

2.3.1.5. CFF Carbon Calculator

The Farm Carbon Calculator (CFF Carbon Calculator, 2012) is a not-for profit online tool which places a strong emphasis on organic agriculture. The livestock section of the model appears to be based on standard Tier I methodology (IPCC, 2006), though this is not specifically stated.

The model has the capability to assess GHG emissions from fuel and electricity use, material consumption, crop production/importation, fertiliser use, enteric fermentation and manure management. There is the facility to assess emissions associated with building materials and capital items such as farm machinery. There are functions to assess post farm gate haulage emissions, and to assess carbon sequestration by woodland, orchards, hedges and field margins.

Little emphasis is placed upon N_2O emissions (Whittaker et al., 2013). Where these are associated with crop residues, they are considered in the model; however, the calculations take no account of N_2O emissions from fertiliser spread or from manure. The tool as a whole does not hold PAS2050 certification.

Table 2.2 Summary of emissions sources included by the tools. Note that this table is not intended as an exhaustive list of farm-level emissions sources, but is tailored to the tools and input data. *Y* = included, *N* = not included, *?* = unclear.

		AgRE Calc	Cool Farm Tool	CALM	CPLANv0	CFF
Crop residues	N_2O	Y	Y	Y	Y	Y
Manure application	N_2O	Y	Y	Y	Y	N
Fertiliser application	N_2O	Y	Y	Y	Y	N
Lime/urea application	CO_2	Y	Y	Y	Y	N
Manure management	CH_4	Y	Y	Y	Y	Y
	N_2O	Y	Y	Y	Y	N
Enteric fermentation	CH_4	Y	Y	Y	Y	Y
Fertiliser	(embedded)	Y	Y	Y	?	Y
Feed	(embedded)	Y	Y	N	N	Y
Bedding	(embedded)	Y	Y	N	N	N
Pesticides	(embedded)	Y	Y	N	N	Y
Plastics	(embedded)	Y	N	N	N	Y
Diesel	CO_2	Y	Y	Y	Y	Y
Electricity	CO_2	Y	Y	Y	Y	Y
Woodland (sequestration)	CO_2	Y	Y	Y	Y	Y

2.3.2. Data acquisition

Sample data for seven farms was sourced from within the repository of Scotland's Rural College (SRUC); these represented a mix of SRUC-owned farms and independent affiliated enterprises from different regions across Scotland. In selection, emphasis was placed on beef production; this in part reflects the high environmental impact of beef as compared to other livestock enterprises (Eshel et al., 2014), and provides a link between each of the farms for comparison of emissions intensity.

The farms nevertheless contained a mix of additional enterprises, and are summarised below, with table 2.3 presenting the standing herds and output from each enterprise.

Farm A comprised of a total of 1,015 ha, with 939 ha a mix of hill, upland and lowground grazing. Arable crop production on the remainder partially supplied the feed requirements of the livestock. The farm ran cattle in a breeder/store system with around 200 suckler cows, and a mixed hill and lowland sheep system with 1,200 ewes.

Farm B produced winter wheat, winter barley, spring barley and oats on 242 hectares of land. An additional 282 hectares were under grass to support the beef enterprise, which comprised a herd of around 300 Limousin cross suckler cows, with all progeny finished on the farm.

Farm C had a large dairy herd with around 250 milking cows. A smaller beef enterprise drew on the dairy herd, and a flock of around 312 ewes produced 500 lambs for sale annually.

Farm D comprised a suckler beef unit of around 100 cows, and a sheep unit of around 300 ewes which produced around 500 lambs for sale annually. A large pig unit of comprising approximately 650 adults and 2,000 juveniles was also present. Around 92 hectares of crops were grown to support the livestock enterprises.

Farm E was an upland beef and sheep farm, comprising a beef herd with 140 suckler cows, and two sheep flocks comprising 800 ewes in total. Around 8 hectares of land was used to grow forage crops to support the livestock enterprises.

Farm F was a 329 hectare organic dairy farm comprising a herd of 170 dairy cows. The business retained all of the offspring from the dairy herd, and finished around 100 head of cattle for beef annually. Additionally, 56 hectares of land was devoted to arable production, supporting the livestock enterprises.

Farm G comprised a flock of around 250 Dorset cross ewes, 30 mixed breed suckler cows and a varying number of finishing cattle bought as stores or weaned dairy calves from other organic units. Around 20 hectares of cereals were grown to provide winter feed for the livestock. Livestock were finished on farm.

Carbon footprinting data characterising these farms was collected by SAC Consulting for calendar year 2014, except for farms E and F, where data availability necessitated the use of 2013 data. Boundaries for system characterisation were cradle to farm gate.

Table 2.3. Annual herds, land areas and outputs for farms A – G, based on the sample data. The values given in head refer to the average number over the footprint year, and hence reflect a) the individual year in question, and b) the proportion of the year spent on the system by each livestock category.

			Farm A	Farm B	Farm C	Farm D	Farm E	Farm F	Farm G
Beef cattle	Cows	Head	266	274	8	100	146		28
	Bulls		5	7	1	4	6		1
	Heifers		116	213	17	133	108	64	48
	Steers/male entire[1]		222	199	22	63	57	143	79
Sheep	Rams	Head	42		26	10	34		12
	Ewes		1,203		312	310	783		265
	Juvenile		948		94	168	600		40
	Lambs		900		240	294	644		300
Dairy cattle	Cows	Head			257			173	
	Bulls				1			2	
	Heifers				149			139	
	Steers				38				
Pigs	Adult	Head				659			
	Juvenile					2,080			
Land	Rough grassland	Hectares	622	7.3		24.1	788	35.1	128.2
	Improved grassland		314	173.3	194.2	145.8	188	184.6	78.4
	Arable		49.7	243.3	54.6	91.9	8	55.9	19.8
	Woodland		11.8		16.2	30.1	33.3	51.4	80.8
Sales	Beef suckler cows	kg live weight	17,342	34,104	1,300	7,700	12,826		
	Beef bulls		1,500			1,250	1,044		
	Beef heifers		77,803	49,579	1,500	20,376	19,494	39,078	9,680
	Beef steers		77,803	69,687	3,120	24,050	27,813	29,880	26,000
	Beef male entire[1]		3,960	21,000					
	Ewes	kg live weight	19,800		1,440	3,975	18,200		3,740
	Rams		425		0		300		255
	Lambs		41,589		23,000	24,940	55,440		10,955
	Dairy cows	kg live weight			3,404			18,690	
	Dairy bulls				650			565	
	Dairy male entire[1]				118,750				
	Sows	kg live weight				2,322			
	Boars					230			
	Finishing pigs					814,200			
	Wool	Tonnes	4.72		0.83	0.71	3.19		0.78
	Milk				1,978			1,315	
	Barley	Tonnes		921					
	Oats			86					
	Wheat			461		524			
	Oilseed rape					56			

[1] The male entire categories refer to uncastrated juvenile male dairy/beef cattle.

2.3.3. Data preparation and processing

The following data categories were supplied for each farm by the raw datasets:

- Land use category and area
- Arable yields by crop type
- Fertiliser and pesticide usage, type and application rates
- Livestock age, class and performance data
- Livestock feed types, quantities and provenance
- Manure management system types and usage
- On farm electricity and fuel use (at enterprise level)

To provide a baseline for comparison of outputs from the different models, manual estimates were calculated for emissions stemming directly from livestock (CH_4 enteric fermentation and N_2O manure deposition and management). This was done according to Tier I and II level methodology as specified in the IPCC (2006) Guidelines.

Summarising the approach, Tier I manual calculations used default emission factors for western Europe for emissions from both enteric fermentation and manure. By contrast, the Tier II calculations followed the energy-based calculations as stipulated by the Guidelines, and made use of all activity data present in the sample datasets. Additionally, an online database resource, Feedipedia (2012) was used to provide data for calculating the digestible energy and crude protein in the diet (DE% and CP%) at enterprise level, a required input for Tier II level calculation.

An emissions intensity estimate, in kg CO_2-eq / kg beef Live Weight (LW), was derived from the farm level results. In order to calculate this, it was necessary to allocate the emissions which formed the whole-farm estimate to different enterprises on the farms. However, with the exception of AgRE Calc, none of the sampled tools allocate emissions within the farm footprint.

AgRE Calc contains integrated protocols for the allocation of emissions to the end user enterprise wherever resource transfer (such as the provision of home-grown feed to livestock) occurs on farm. While other tools do allocate, this occurs only at the farm gate. In the case of co-production in AgRE Calc (such as cereal grain and straw), allocation of emissions to products is based on economic value. For AgRE Calc, emissions as calculated for the beef enterprise were utilised. For estimates from other tools, in the absence of an integrated approach, the enterprise allocations as calculated by AgRE Calc were applied as a ratio through which gross emissions estimates were processed. To derive the emissions intensity, the annual beef enterprise footprint was divided by the beef LW sales, providing an emissions intensity estimate in kg CO_2-eq / kg beef LW.

2.4. Results and discussion

2.4.1. Whole-farm GHG emissions

A total of 35 emissions estimates were calculated from the seven datasets and five tools. The data allowed for complete footprints to be produced from each tool, with two partial exceptions, Firstly, CPLANv0 did not appear to include embedded emissions estimates for any sources (Section 3.3.2). Secondly, the Cool Farm Tool required more detail than was available in the sample data in order to produce an estimate for woodland CO_2 sequestration (Section 3.3.4). Including CO_2 sequestration by woodland, results ranged from −6.67 (CALM Tool, Farm G) to 3.89 kt CO_2-eq year^{-1} (AgRE Calc, Farm A). Excluding sequestration, these totals ranged from 0.15 (CPLANv0, Farm G) to 4.02 (AgRE Calc, Farm A). Whilst this represents, to some extent, the actual variability in farms, a considerable amount is attributable to the tools themselves (Table 2.4).

Table 2.4. Gross farm-level GHG footprints (in kt CO_2-eq year^{-1}) as calculated by the five sample tools. Sequestration of CO_2 by woodland (negative) is not included in these totals.

Farm	AgRE Calc	Cool Farm Tool	CALM	CPLAN v0	CFF Calculator	Mean	Range
A	4.02	2.92	2.99	0.77	3.01	2.74	3.25
B	2.69	2.82	2.49	0.64	2.84	2.29	2.2
C	3.53	2.29	2.61	0.75	2.58	2.35	2.78
D	3.36	2.4	1.94	0.35	2.16	2.04	3
E	1.93	1.87	1.59	0.42	1.51	1.46	1.51
F	1.98	1.61	1.63	0.56	1.91	1.54	1.42
G	0.61	0.47	0.42	0.15	0.53	0.44	0.46

Even with results fully aggregated, it is apparent that some tools are following markedly different approaches to the process of farm-level GHG accounting (Fig. 2.1). The CPLANv0 tool appears consistently below the general trend. AgRE Calc produced the highest results on average. A partial grouping is apparent, with results from CALM, the Cool Farm Tool, the CFF calculator and, to some extent, AgRE Calc, following a similar pattern.

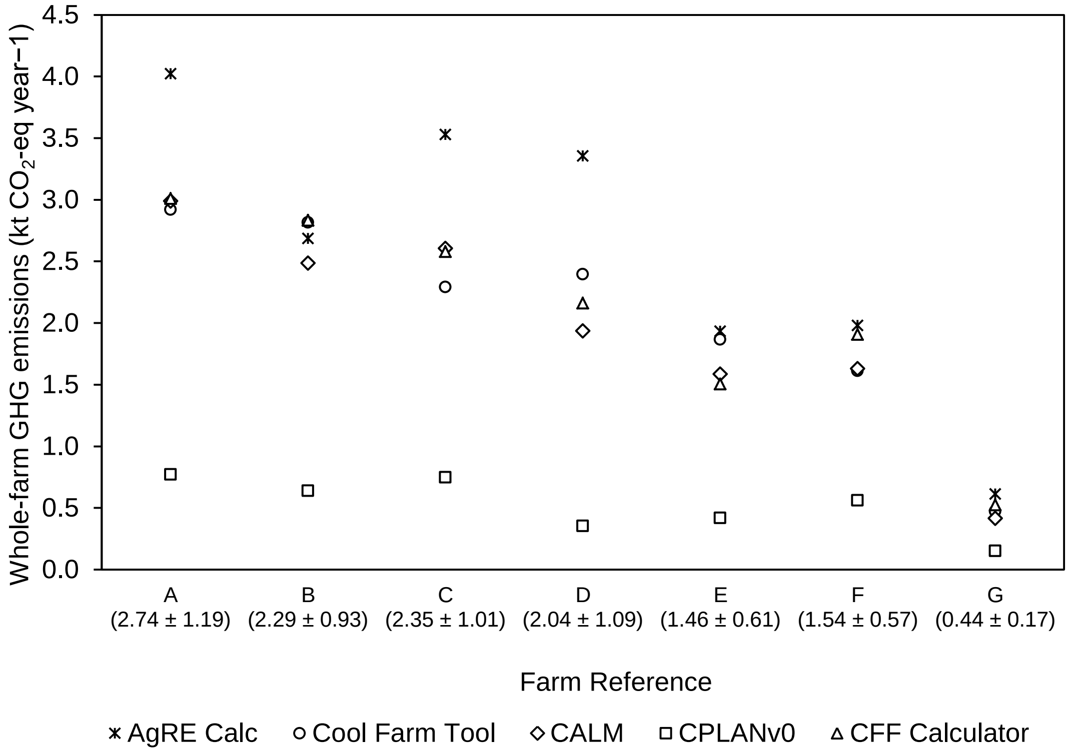

Fig. 2.1. Total GHG footprints for each of the five calculators over the seven sample farms. Sequestration of CO2 by woodland, deductible from the footprint, is excluded from the totals in this figure. The calculated mean estimate from the five tools ± 1 S.D. are shown in parentheses.

Tool variability was reasonably consistent relative to the magnitude of the estimate. Estimates for Farm D were somewhat more variable, however; a large pig enterprise dominates output for this farm (Table 2.3), implying higher levels of inconsistency in the way that emissions were calculated for this livestock type.

Between 5 and 14 (*Mdn* = 10, *N* = 35) individual sources made up the total emissions estimate for each farm. This highlights an issue inherent in farm-level footprinting; with every additional emission source included in the estimate, the number of potential causes for methodological variability in the final footprint increases accordingly.

As such, it is entirely possible for the composition of estimates to differ without affecting the final value of the farm-level footprint. The insight which can be gained by examining the footprints at farm-level is therefore limited, and to further explore the model methodology, the following sections examine these estimates at category level.

2.4.2. Livestock emissions

Direct emissions from livestock represented the largest overall emissions category, contributing between 43% and 92% (*M* = 72%, *N* = 35) to the overall farm-level footprint. As such, emissions from this source are broken down into the two contributing subcategories (enteric and manure emissions) for analysis. Included in this assessment were estimates from all five tools, as well as manually calculated Tier I and II estimates (Fig. 2.2).

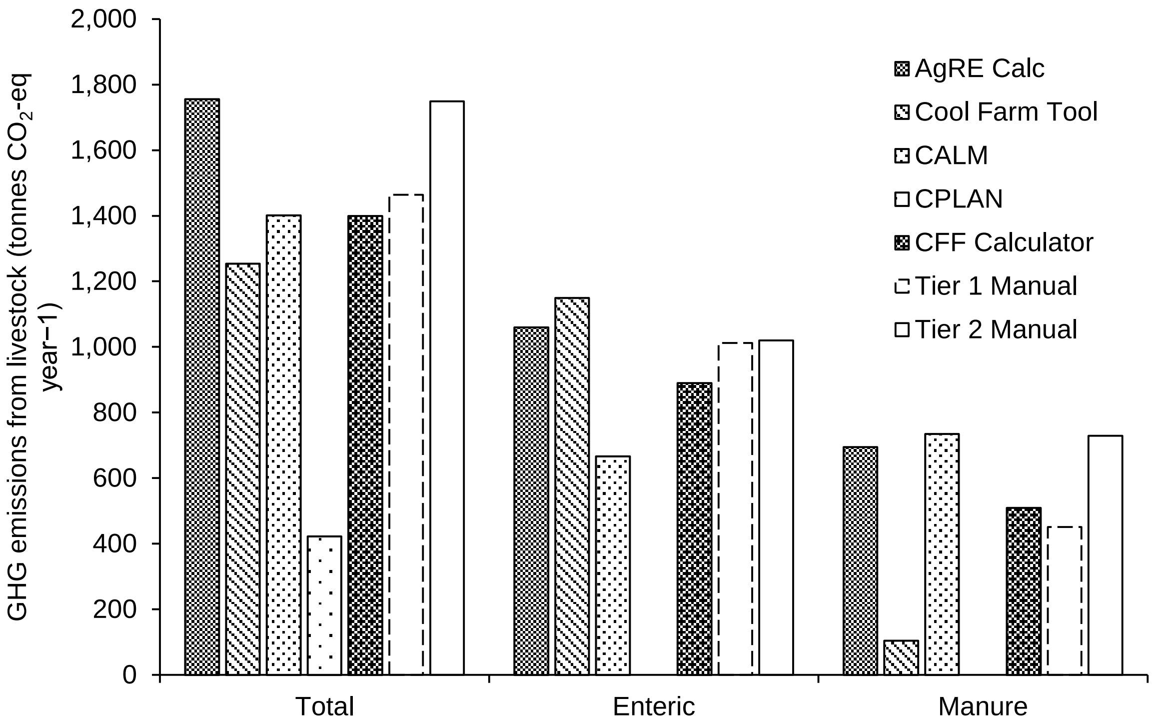

Fig. 2.2. Graph showing mean livestock emissions estimates (N = 7) for each of the tools and manual calculations, including a breakdown into subcategories. The CPLANv0 calculator did not produce results at subcategory level and hence only the total is shown for this tool.

The Tier I and II manual calculations show consistent disparity across the sample farms. Tier I methodology gave lower total livestock emissions as compared to Tier II level calculations for the farms included in this study (Fig. 2.2). Further examination of results indicated that manually calculated Tier I estimates ranged from 74.7% – 98.6% of their Tier II counterparts (M = 84.5%, N = 7).

Examining the breakdown of these emissions into subcategories, it appears that the difference between the Tier I and II methodology stems from the estimate of manure emissions (Fig. 2.2). One explanation for this lies in the fact that Tier I methodology employs activity data for manure management system usage which is generic to western Europe. Manure management systems vary considerably, and so if this data does not accurately represent the sample farms, it could lead to the disparities shown here.

2.4.2.1. AgRE Calc

A close correspondence can be observed between AgRE Calc and the manual Tier II calculations. For manure calculations, AgRE Calc differs from the manual Tier II approach in that it uses expert-supplied reference data to calculate the N content of manure (SRUC, 2014); this factor directly impacts N_2O emissions and can affect the total emissions substantially. This approach reduces data demand, an important consideration for farm-level tools. The close match to Tier II, for which N content was manually calculated, suggests that this is one area in which data demand may be reduced without unduly impacting results, though doing so limits the flexibility of the estimate.

2.4.2.2. The Cool Farm Tool

Hillier et al. (2011) followed IPCC (2006) Guidelines for the calculation of livestock emissions within the Cool Farm Tool, which is stated to perform at either a Tier I or Tier II level depending upon the availability of data. Sample data for all farms was sufficient to perform a Tier II estimate. Overall, however, results from the Cool Farm Tool undervalue livestock emissions as compared to the average totals for both Tiers of calculation (Fig. 2.2). This difference stems from the estimate for manure emissions. The Cool Farm Tool underestimates manure-related emissions as compared to both methodological Tiers, and to other tools. The reasons for this are unclear; given the methodological description by Hillier et al. (2011), the estimates would be expected to lie close to the Tier II manual estimates.

The relative contributions from subcategories to the livestock total are, for this tool, in stark contrast to other methodologies; at the livestock category and whole farm level, however, the Cool Farm Tool does not differ substantially (figs. 2.1 and 2.2). Whilst the total result is unaffected, this means that the Cool Farm Tool would be likely to respond differently to changes in the livestock system, as compared to other tools.

2.4.2.3. The CALM Tool

Total livestock emissions as estimated by the CALM tool are similar to the manual Tier I calculations (Fig. 2.2). However, further breakdown reveals that the CALM Tool underestimated enteric emissions as compared to both Tiers. By contrast, the CALM tool's estimate of manure emissions was similar to Tier II. One possible explanation for this is that the CALM tool, though using a Tier I emission factor, calculates emissions based on farm-specific activity data. This may have captured some variability in manure emissions missed by the manual Tier I approach.

The CALM Tool was the only model to estimate, on average, higher manure-related emissions as compared to enteric emissions, apparently through underestimation of the latter. While methodology behind this is unclear, the response of the CALM calculator to livestock system changes would likely different to other tools for this reason.

3.4.2.4. CPLANv0

Total emissions as estimated by the CPLANv0 calculator fell starkly below those of all other tools and both manual calculations (Fig. 2.2). This is result is striking given the statement by the tool developers that the CPLANv0 tool follows IPCC (2006) methodology throughout (SEE360, 2007). The CPLANv0 tool presented results in highly aggregated format, and as such it was not possible to derive a breakdown for the livestock emissions category, hindering further speculation as to the methodology employed.

2.4.2.5. The CFF Calculator

The CFF calculator produced an average total emissions estimate which did not differ greatly from the Tier I methodology. Further examination of the breakdown of this estimate would suggest that the methodology closely mirrors the approach taken by the manual Tier I calculation.

The CFF Calculator produced results for manure which did not differ substantially from the Tier I manual calculation. In one sense, this is surprising in that Whittaker et al. (2013) state that the only source of N_2O included by the CFF tool is crop residues; however, these authors only assessed this tool in the context of cropping systems, which may account for the difference. It is difficult to confirm this explanation, as the CFF tool does not provide results disaggregated by gas. It is also plausible that an update has taken place since the study by Whittaker et al. (2013). Lack of methodological transparency such as this makes it difficult to predict how a tool will react to system changes.

2.4.3. Emissions from other sources

Emissions from sources other than livestock were assessed in the following categories, defined as 1) Land and Crops, 2) Embedded Emissions, 3) Fuels, and 4) Sequestration. Note that the fuels category includes emissions from electricity production and fossil fuel extraction, in addition to direct emissions. The average estimates for these categories are presented graphically in Fig. 2.3.

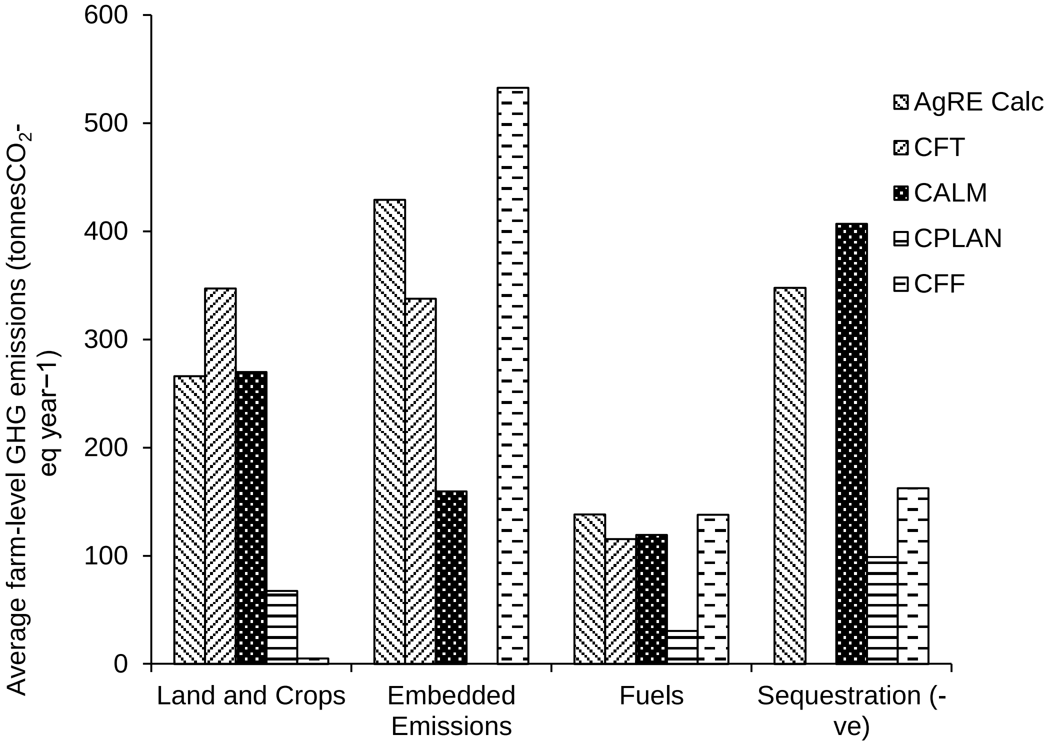

Fig. 2.3. Average emissions for the seven sample farms, disaggregated by source category, as calculated by each tool.

2.4.3.1. Land & crops

Emissions estimates were found to be highly variable for the Land & Crops category. In contrast to the low result produced by the Cool Farm Tool for manure emissions, the emissions estimate from land and crops exceeded that of all other calculators (M = 347,224 kg CO_2-eq year^{-1}). In comparison to the Tier I methodology employed by AgRE Calc and the CALM tool, the Bouwman et al. (2002) model employed by the Cool Farm Tool appears to have predicted slightly higher emissions than the IPCC methodology. Whilst the reasons for this are unclear, the Bouwman model captures greater variability in soil conditions than the Tier I approach, which may explain the difference in emissions.

Markedly lower than the general grouping were estimates by CPLANv0 and the CFF Calculator. For CFF Calculator, this difference is explicable, as the tool excludes all sources of N_2O emission with the exception of crop residues (Whittaker et al., 2013). This omission is substantial, with the mean land and crop estimate from the CFF Calculator (M = 5.19 tonnes CO_2-eq year^{-1}) only 2.7% of the value of the mean estimate across all other tools (M = 191.24 tonnes CO_2-eq year^{-1}).

The CFF Calculator estimates embedded emissions at a level much higher than the general grouping. It is possible that some of the 'missed' N_2O emissions are incorporated into this category, though without further methodological information or disaggregation of results it is not possible to confirm this speculation.

These omissions are likely to affect how the CFF Calculator responds to mitigation options designed to reduce N_2O emissions from land and crops. Optimisation of fertiliser application (and avoidance of over-applying) has been found to be a viable and cost-effective mitigation measure (Domingo et al., 2014); through excluding of this source of N_2O, the CFF Calculator would underestimate the effects of this.

It is unclear as to why results from the CPLANv0 calculator were consistently lower than the general grouping; the information supplied by the developers appears to suggest that the methodology follows IPCC (2006) Guidelines. Impeding further investigation is the fact that results from this tool are not disaggregated by source category.

2.4.3.2. Embedded emissions

Estimates of embedded emissions varied considerably, and were the largest emissions category after livestock (Fig. 2.3). The CPLANv0 calculator was exempted from this assessment, as it did not appear to consider embedded emissions from any sources, though a lack of disaggregation of results made it difficult to ascertain this in the case of fertiliser.

Differences of scope between tools can explain a large amount of this variation (table 2.2). Where possible, the scope was determined from information supplied by the tool developers; however, it was frequently necessary to infer this information from data input requirements.. Consistent scoping of farm-level tools, particularly in the context of embedded emissions, represents a challenge for developers. These results make it clear that until such a consensus is reached, is important for users to be aware of the impacts this can have on total estimates.

2.4.3.3. Fuels

Whilst showing some variation, emissions estimates were relatively consistent between tools, with the exception of CPLANv0, which markedly underestimated by comparison (Fig. 2.3). Except to note that low estimates appear to be typical of the CPLANv0 tool, it is difficult to ascertain why this may be, as the developers did not state which methodology was applied.

For the Cool Farm Tool and AgRE Calc however, the methodology used to compute emissions from this source is known; Hillier et al. (2011) state that the Cool Farm Tool uses and EcoInvent database (Ecoinvent Centre, 2007), whilst AgRE Calc uses the publicly available DEFRA/DECC (2011) Emission Factors for Company Reporting (SRUC, 2014). These tools provided similar average estimates, whilst the CALM Tool and CFF Calculator provided estimates which, though of uncertain provenance, were consistent with the group trend.

It is worth noting that the fraction of farm-level emissions stemming from fossil fuel use is not high, varying from 2.5 to 11.0% of the net total emissions for the sample farms (M = 6.2%, N = 35). Consequently, where variability in estimates for this category is minor, it is unlikely to markedly affect the overall total.

2.4.3.4. CO_2 sequestration

Before examining tool results for CO_2 sequestration, it should be acknowledged that the benefits of carbon sequestration by woodland as a tool to offset farm-level GHG emissions are the subject of complex debate (Cannell, 1999). Whilst the full extent of this debate falls outside the scope of the present study, it is considered here as this component of the GHG footprint is universally included by the present sample of tools.

Estimates made by the tools for CO_2 sequestration by woodland biomass also showed considerable disparity (Fig. 2.3). Some explanation for this disparity may well lie in the number of methodologies available to calculate sequestration by woodland, with methodologies provided by the US Forest Service, UK Forestry Commission as well as the IPCC (2006) Guidelines. The latter has been adopted by both AgRE Calc and the CALM tool.

As a global methodology, the IPCC (2006) Guidelines supply limited data for temperate woodlands. Estimates of sequestration from AgRE Calc ($M = 405.7$ tonnes CO_2 year^{-1}, $N = 7$) and the CALM tool ($M = 474.8$ tonnes CO_2 year^{-1}, $N = 7$) exceed others by a considerable margin; it may be that the lack of data has led to generalisations which overestimate CO_2 sequestration as compared to other methodologies. Comparison with an estimate manually produced for the seven farms using the (UK-specific) Forestry Commission's Carbon Lookup Tables (West & Matthews, 2012) ($M = 269.2$ tonnes CO_2 year^{-1}, $N = 7$), falls closer to the lower estimates from other tools, supporting this speculation.

The CFF Calculator produced the median estimate for this category ($Mdn = 189.6$ tonnes CO_2 year); whilst this value is somewhat lower than the Forestry Commission-derived estimate, the references given for the tool (CFF, 2012) suggest that this source was used by the developers. This being the case, the disparity between the manually calculated estimates ($M = 269.2$ tonnes CO_2 year^{-1}) and the results of the CFF Calculator ($M = 189.6$ tonnes CO_2-eq year^{-1}) demonstrates the consequence of differing interpretations of this methodology.

The Cool Farm Tool's sequestration assessment required input of species composition and trunk diameter change over a one-year period. The available data did not allow for this level of detail, and assumptions made in this respect can significantly influence results. As such, comparison to other tools would have limited validity, and the decision was made to avoid producing a potentially misleading estimate. Users of the Cool Farm Tool without access to specialist forestry data would face a similar decision.

The sequestration estimate of the CPLANv0 tool, whilst low, was higher in relative terms compared to its estimates for other emissions sources. Thus, the balance of emissions vs. sequestration reported by this tool is likely to differ in comparison to other tools. Where sequestration is used to offset emissions from other parts of a farming system, this difference will substantially affect how that system is seen to perform.

Several tools went into greater depth in this area than could be explored using the sample data. The Cool Farm Tool has the ability to assess emissions/sequestration from land use change (LUC) for up to a maximum of 20 years; AgRE Calc does not consider emissions arising from land use change. The Cool Farm Tool also considers sequestration arising from changes in tillage practice and use of cover crops. The CFF Calculator considers sequestration not only from woodland, but also from single trees, hedges, field margins, orchards, vineyards, soil and wetlands. The CPLANv0 tool has the facility to assess emissions/sequestration from LUC since the year 1957 in addition to forestry. Finally, whilst the CALM calculator limits its approach to woodland, it includes the facility to assess managed woodland in detail according to species, age and management strategy. Whilst it was not possible to empirically assess the effect of these differences in scope using the sample data, it is certain that the output would be affected. This difference may be substantial, depending upon the extent of these features in a given system.

2.4.4. Emissions intensities and allocation

GHG emissions intensities for beef production, in kg CO_2-eq kg beef LW^{-1} were calculated for each farm (N = 7) and each tool (N = 5) as described in Section 2.3, creating a total of 35 estimates.

The mean emissions intensities calculated by the tools (Fig. 2.4) show some similarity to those published in LCA literature. It is important to note that the LCA estimates shown are based on studies of a range of systems and scales and so direct comparisons should be made with extreme caution; however, broadly speaking this similarity does appear to indicate some consistency in approach between LCA practitioners and developers of these farm-level models.

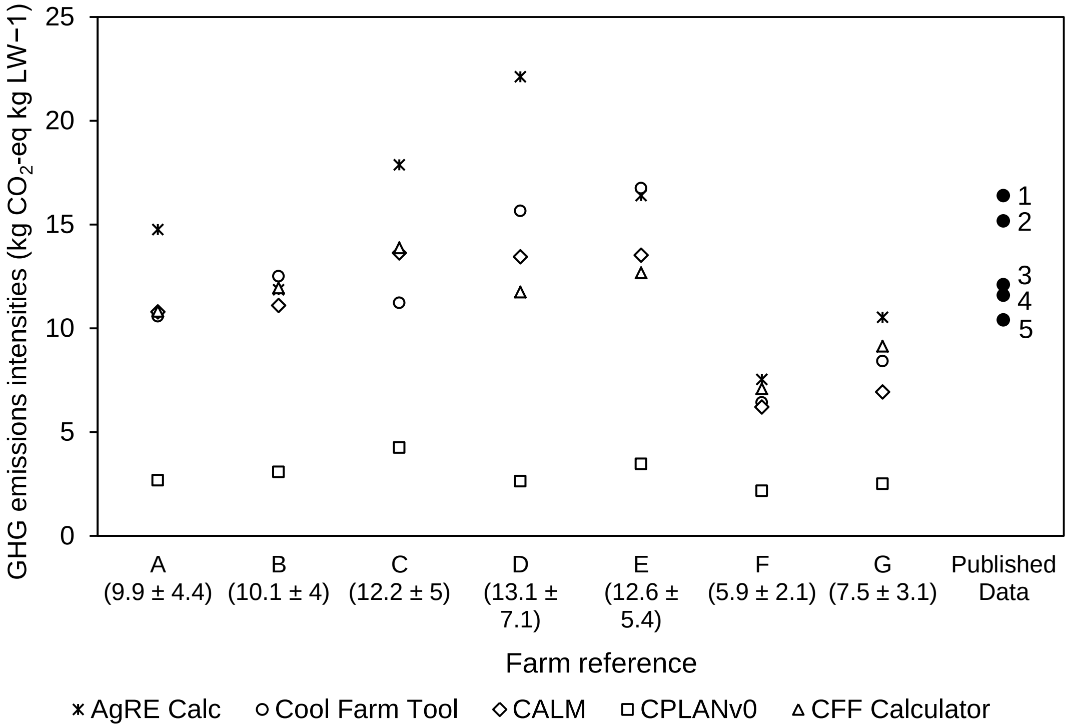

Fig. 2.4. Emissions intensities calculated for each farm and tool (N = 35). The calculated mean estimate from the five tools ± 1 *S.D.* are shown in parentheses. Emissions intensities from a range of published LCA literature are shown in the final column, for which the sources are 1) Nguyen et al. (2012) (a calculated average from four systems); 2) Vergé et al. (2008); 3) Beauchemin et al. (2011); 4) Vergé et al. (2008); and 5) Casey & Holden (2006). For values 1) and 3), a conversion factor of 1/0.55 (Opio et al., 2013) was applied to convert the published values from kg Carcass Weight (CW) to kg Live Weight (LW).

Farm D showed the greatest mean emissions intensity (M = 13.1 ± 7.1 kg CO_2-eq kg LW^{-1}), though this was not markedly larger than the highest published values. It is likely that the magnitude of this estimate is a result of the intensive nature of this farming system. The high variability in estimates for this farm is likely to stem from the large pig unit present in the system; when assessing the whole-farm estimates (Section 3.1) it was noted that the tools varied considerably in the estimates produced for this enterprise. More generally, a higher range for the emissions intensity appears to correspond to systems showing a more complex array of enterprise types.

The relatively low mean estimate for Farm F (M = 5.9 ± 2.1 kg CO_2-eq kg beef LW^{-1}) is likely to stem from the fact that the main output for this farm is a dairy enterprise, the offspring from which are retained and finished for beef. This is not directly comparable with the published values (Fig. 2.4), which relate to dedicated beef systems. Here, the majority of emissions from breeding animals are associated with the dairy enterprise, and the system avoids the overheads present in a typical suckler system. Farm G (M = 7.5 ± 3.1 kg CO_2-eq kg beef LW^{-1}) is a typical suckler system; emissions from this enterprise are low due to an avoidance of inputs such as fertiliser and pesticides. As a consequence of this, the tools which produced the highest results for this farm were those which, on average, attributed the greatest values to enteric emissions estimates (AgRE Calc, CFF and the Cool Farm Tool). The estimates of these tools were comparable to the lower bounds of the published data (Fig. 2.4).

The CPLANv0 tool consistently forms the lower bound of estimates. The average emissions intensity, as calculated by this tool across the enterprises ($M = 3.0$ kg CO_2-eq kg beef LW^{-1}, $N = 7$) falls far below any of the published values shown in Fig. 2.4, indicating a significant methodological disparity between the CPLANv0 tool and these studies. AgRE Calc typically forms the upper bound of estimates; this is likely due to a number of factors identified thus far. Use of IPCC (2006) Tier II level methods for calculation of direct livestock emissions is likely to have increased this part of the estimate above those tools which follow Tier I methodology. Additionally, AgRE Calc was shown to have the broadest scope for the embedded emissions sources present in the sample datasets; thus, inclusion of these likely further increased the estimate beyond other tools. The Cool Farm Tool, the CALM Tool and the CFF Calculator are generally relatively closely grouped, though the order of this grouping varies somewhat between farms (Fig. 2.4). In neglecting major sources of N_2O from the estimate, the CFF Calculator is relatively low for farms where N fertiliser use is high (e.g. Farms D and E), though high estimation of the magnitude of embedded emissions may counter this to some extent. Where enteric emissions make up a higher proportion of the total, the CALM Tool appears to fall below the general grouping due to the lower emphasis it places on this emissions source (e.g. Farm G).

2.5. Conclusions

The broad range of sample data allows for some consideration of tools' fitness-for-purpose in the context of footprinting livestock systems. In the absence of an accepted, harmonised methodology for farm level tools, this discussion will avoid making explicit recommendations on tool fitness-for-purpose, but will seek to explore possible criteria for this in the light of tools' performance on real-world livestock enterprises.

2.5.1. Tool transparency

In any such application, transparency of tool methodology is an important consideration, accounting for inevitable variation and allowing informed comparisons to be made. A lack of transparency in methodology was found to be a major issue for several tools, limiting the insights which could be gained. Hillier et al. (2011) took steps to address this through publication in the case of the Cool Farm Tool, though in some cases it remains unclear what method is being followed. Developers of the CALM Tool and CFF Calculator provided some information on methodology, though lack of detail made it difficult to assess exactly how results were calculated. Developers of the CPLANv0 tool stated that IPCC (2006) Guidelines were used but gave no further information as to additional sources of methodology. Seeking to address this issue for AgRE Calc, methodological sources for this tool are presented for the first time in this paper (Section

2.1.1). Methodological transparency and availability of information is likely to be a key concern where these tools are sought to inform policy (Hall et al., 2010), and hence is a potential limiting factor in the uptake of tools by policy makers. It may also limit the extent to which users can employ the tools make informed decisions on mitigation of emissions from farming systems.

2.5.2. Tool methodology

Studies have demonstrated the importance of nitrous oxide emissions from cultivation of palm oil and sugar cane (Keller et al., 2014), wheat (Whittaker et al., 2013), and several additional cereal cultivation scenarios (Lewis et al., 2013). This study shows the same is true in the case of livestock systems, not least because such systems are likely to feed the livestock enterprise. Estimates of land and crop emissions by the CALM tool, the Cool Farm Tool and AgRE Calc showed reasonable parity in the results, whilst those of CPLANv0 and the CFF tool were considerably lower. In the case of the CFF tool it is known that the developers omitted several sources of N_2O (Whittaker et al., 2013), which accounts for the low estimate; for the CPLANv0 tool, the reason for this is not known since IPCC methodology is stated to have been followed. Users should be aware that omissions or underestimation of this emissions source may significantly affect the size of the overall footprint. Additionally, where these tools are employed as decision aids for measures aimed to reduce N_2O emissions, the efficacy of such approaches may be underestimated.

Estimates of emissions from livestock and manure showed reasonable parity between tools, with the exception of CPLANv0, which again markedly underestimated. Results from the study data show this to be the largest emissions source with the potential to significantly impact results if inconsistently handled. Calculated emissions from manure showed most variability within the category, which may be due to differing interpretations of the IPCC (2006) guidelines and manure storage categories. The Cool Farm Tool (Hillier et al., 2011) showed the most notable difference in this area. The implications of this are important for users to recognise, given that manure has been shown to offer considerable mitigation potential both in terms of diet (Mathot et al., 2012) and storage management (Masse et al., 2008). Where it is unclear precisely how these emissions are calculated, users should be wary of employing tools to estimate the efficacy of related mitigation measures.

Calculation of embedded emissions (emissions from production of agrochemicals and feeds) varied considerably and in some cases represented the second largest emissions category behind livestock. The differing scopes of assessment for this category (section 3.3.2) appear to be largely responsible for these differences. Harmonisation of tool methodologies in this respect should be a key aim for those with development oversight, and users should be aware of the impact such disparities can have on the footprint. Crucially, in the context of decision-making for cleaner production, omission by some tools of certain embedded emission sources may lead to false economies through uneven consideration of trade-offs.

Emissions from fuel and electricity, as estimated, were relatively consistent between tools, again with the exception of CPLANv0. As the smallest emission category, it appears the slight differences present here are not of great concern to tool users, though as with embedded emissions, the consideration of this category may be important to prevent false economies of mitigation.

Considerable variation, reflective of disparity in the methodologies employed, was present in the estimation of CO_2 sequestration. In particular, the IPCC (2006) methodology, as applied by two tools, appears to be insufficient to account for much variation in British woodlands, and overestimates CO_2 sequestration at least with respect to other, country-specific methodologies. The issue of variable methodologies is exacerbated given that the efficacy of GHG offset through biomass sequestration is not clear-cut (Cannell, 1999), and the complex nature of this component is at odds with its simplistic "positive vs. negative" representation in the tools. In the context of biomass sequestration as a tool to aid cleaner production, this simplification is a very important consideration for tool users and policy makers to be aware of. For the tools, a level of consensus on both the scope of assessment for CO_2 sequestration, and on the methodology employed, would be advantageous.

Finally, it is worth noting that no tools provide estimates of uncertainty alongside the footprints produced. From a scientific standpoint, simplistic GHG modelling such as this carries significant uncertainty; however, this is complex to calculate and interpret, and may not be relevant to the aims of many users. However, it is important to be aware, particularly if tools are employed to guide policy decisions, that even where methodology is transparent, estimates nonetheless carry a degree of uncertainty.

2.5.3. Allocation within tools

For benchmarking applications, or to facilitate comparisons between farms, it becomes necessary convert the farm-level estimate into a standardised functional unit (e.g. kg CO_2-eq / kg product). Allocation of emissions is a key issue in this respect, with complexity of typical livestock systems amply demonstrated by the sample data. Cropping enterprises footprinted by previous tool reviews considered only single-output enterprises and hence did not encounter this issue.

In more complex systems, where a farming system produces more than one product type, tool users must allocate emissions between enterprises in order to separate the product footprints. This may be beyond the skills of an average user, and decisions made at allocation stage have been shown to significantly affect results (Nguyen et al., 2012); thus, it is advantageous that it be performed according to standardised, transparent methodology by the tool itself. Since cleaner production aims are likely to focus on product emissions intensity, rather than farm-level footprint, the ability to consistently separate footprints for mixed enterprises is important. Those with oversight on tool development should be aware of this requirement, and users should be aware of this issue where tools are used to inform decisions or policy. Whilst the requirement to allocate is recognised by some tool developers, the only tool in the current sample with the capability to perform this operation was AgRE Calc.

2.5.4. Final summary

It has been well recognised that the broad scope of farm-level tools such as these represents a considerable strength (Schils et al., 2007), and their performance in the context of this assessment exemplifies this; however, to obtain this advantage requires the compilation of a broad range of methodologies. This study highlights the hazards associated with such an approach, particularly where tool transparency is lacking. Previous reviews have highlighted, in the context of crop production, the requirement to harmonise tool methodology for consistency in results. This study backs that conclusion in the context of livestock enterprises, and the conclusions presented herein provide a decision aid for users to select an appropriate tool for their required purpose. This study additionally finds that even where estimates appear consistent, variation in the component parts of an estimate may exist independently of variation in the whole. Tools may therefore react differently to changes in the modelled system, and as a result should be used with caution to inform mitigation strategies.

It is important that users of farm-level tools acknowledge these issues and treat results with appropriate caution. Where a tool is sought to assist in the derivation or assessment of cleaner production aims, or for the purpose of influencing or informing policy decisions (e.g. Hall et al., 2010), it is vitally important that variation be accounted for, and that areas of opacity in methodology be recognised. Whether prospective tool users are primary producers or policy makers, this study provides a reference point for tool selection and use. Similarly, it provides a synthesis of the state of the art which will be of use to developers in furthering these tools in their ability to provide consistent environmental assessment and decision support for cleaner agricultural production.

Chapter Three

Summary of developments to the AgRE Calc model

3.1. Characterising cattle rations in AgRE Calc

3.1.1. Rationale and background: cattle diets and greenhouse gas emissions

Section 1.4.3. of the introduction identified that feed intake and dietary composition are two of the most influential factors in determining ruminant performance, enteric CH_4 emission, and N_2O emission from manure (Hünerberg et al., 2014). Enteric CH_4 emissions are a by-product of the breakdown of carbohydrates by methanogenic bacteria (Dong et al., 2006), whilst N_2O emissions from manure are the production of microbial nitrification and denitrification processes (de Klein et al., 2006). Enteric emissions are directly linked to the digestible energy (DE) content of the livestock feed (Dong et al., 2006); rations with a higher percentage of GE as DE (a higher DE%) are digested more efficiently, and hence result in lower levels of enteric methane production and improved animal nutrition. Emissions of N_2O are impacted by a number of factors, such as nitrogen (N) retention by livestock, manure storage type, and soil conditions, but crucially all these are scaled by the N content of the livestock ration (de Klein et al., 2006). Available nitrogen in ruminant feed is delivered as crude protein (CP), and hence the CP content of the ration is an important factor in determining the volume of N_2O emitted from manure. Digestible energy and CP percentage values are therefore primary inputs required by the IPCC Tier 2 level calculations of greenhouse gas (GHG) emission from livestock.

3.1.2. Literature survey: Characterisation of diets in life cycle assessment

Given the influential role of this factor in emissions from beef production, manipulation of cattle diets as a mitigation strategy is an opportunity that has been frequently considered in life cycle assessment (LCA) literature (Doreau et al., 2011; Mathot et al., 2012; Hünerberg et al., 2014). Where it is assessed as a mitigation option, it is typically a trade-off between higher GHG emissions from production of higher quality feed vs. a reduction in enteric emissions from cattle fed on more digestible rations. For LCA studies utilising a Tier 2 approach (e.g. Cardoso et al., 2016), where estimates of ration digestibility or crude protein are published, these tend to be point estimates; some studies, (e.g. Hünerberg et al., 2014), utilise data previously collected from experimental approaches; others (e.g. Pelletier et al., 2010), make estimates based on expert opinion.

There are a number of disadvantages to these approaches. Situation-specific measurements such as those utilised by Hünerberg et al. (2014) are expensive and hence not appropriate for the majority of studies. In the absence of this, it is difficult to accurately estimate DE% or CP% without expert knowledge of the system in question; this limits the ability of LCA practitioners to model systems with which they are not intimately familiar or for which they do not have access to expert opinion. Such experts are typically area-specific, which limits the possibility of international comparisons. There is also limited scope for these estimates to vary in response to changes in animal ration, meaning emissions trade-offs relating to dietary manipulation of the type demonstrated by Hünerberg et al. (2014) are difficult to accurately assess. A primary objective of a tool such as AgRE Calc is to provide a user-friendly framework with which to assess the viability of on-farm GHG mitigation; crucially, such a tool must be flexible, so the typical approach of situation-specific estimates is not viable. Given the sensitivity of the overall footprint to these parameters, and the trade-offs involved, it is expedient to examine the possibility of empirically calculating these primary inputs.

3.1.3. Dietary characterisation in AgRE Calc prior to development

Expert estimates (provided by SAC Consulting) were used to estimate DE% and CP% of cattle diets prior to the implementation of this development. Livestock systems were classified according to type, and dietary DE% and CP% were estimated for each livestock class within each system. This approach was chosen with the aim of reducing data input burden for the user, and it was accepted that the expert estimates would in effect be a representative average for each system type. The disadvantage of this approach, which provided the rationale for this development, is that the estimate-lookup approach provided no opportunity for these parameters to vary based upon modelled system changes. Section 3.1.4 discusses the role of these parameters in the modelled system and their resulting impact on emissions intensity.

3.1.4. Importance of dietary digestibility and crude protein in modelled emissions

In IPCC Tier 2 calculations (Dong et al., 2006), dietary digestible energy percentage (DE%) is an inverse exponential scaling factor for gross energy intake, which in turn directly impacts enteric methane emissions from cattle. Consequently, enteric methane production scales proportionally to the inverse of the DE% raised to the power of two (Fig. 3.1, eq. 3.1).

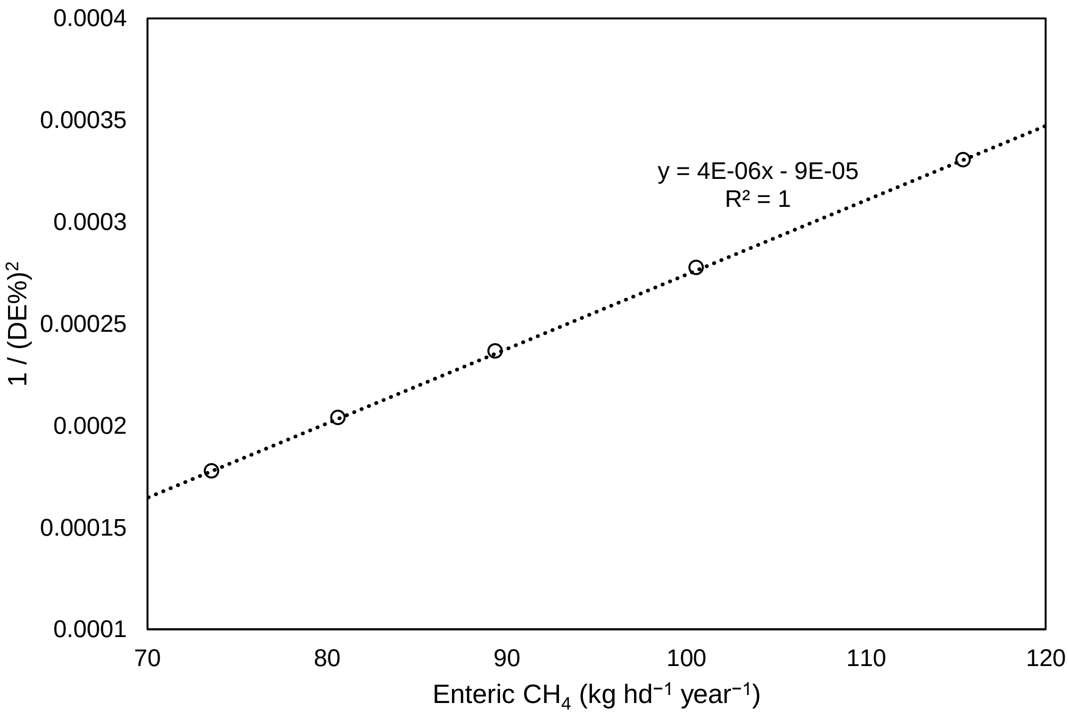

Fig. 3.1. Example showing relationship between enteric methane and digestibility (DE%) of the ration. Example data is modelled using IPCC (2006) Tier 2 guidelines for a single 670kg suckler cow with an assumed Net Energy requirement of 70 MJ day^{-1}. Digestible energy of the diet has been manipulated between values of 55 – 75%.

Equation 3.1. Relationship between enteric methane and digestibility (DE%) of ration.

$$CH_{4\,enteric} \propto \frac{1}{DE^2}$$

Where:
$CH_{4\,enteric}$ = modelled enteric methane production (kg CH_4 hd^{-1} year^{-1})
DE = the ruminant digestible energy (in % of gross energy) in the ration

Consequently, lower digestibility rations have an exponentially higher impact on enteric methane. This non-linear relationship, coupled with the large proportion of the footprint of beef production formed by enteric emissions (Beauchemin et al., 2010), means that DE% as an input parameter plays a crucial role in determining the emissions intensity of a beef production system. Given its potential as a mitigation option, and the trade-off typically incurred where improvement in ration digestibility is sought, it is crucial that a farm-level GHG model should a) accurately account for the ration digestibility of a particular system, and b) have the flexibility to accurately account for changes made to that system in terms of cattle diets.

3.1.5. Modelling digestibility of the cattle ration

The aim of this approach was to improve model accuracy and flexibility without greatly increasing data input burden. The approach therefore aimed to use existing inputs, namely allocation of both home-grown and purchased feedstuffs to the beef enterprise. The model was adapted to provide opportunity to input this at the level of individual animal classes, where previously input was only possible at enterprise level. This had the impact of allowing dietary characteristics to be modelled at class level (necessary given on the non-linear relationship between DE% and CH_4 emission) and, as a secondary improvement, allowed for emissions from feed production to be allocated at class level rather than to the enterprise as a whole. Aside from this development, model input remained unchanged from the previous model versions.

At the simplest level, the digestibility of the overall ration can be accurately represented through calculation of a weighted average the digestibility of the ration components. The basis of the approach is consequently formed of a table of values for DE% (as well as and CP%, dry matter % and gross energy content in MJ kg DM^{-1}) for each of the available ration components. This data was sourced from Feedipedia (INRA, 2012) and the database integrated into the model. The full collated dataset as employed in AgRE Calc can be found in the appendix (tables A.1 and A.2).

The DE% relates to the gross energy (GE) in MJ kg DM^{-1}, and effectively denotes the proportion of this value which is accessible by the ruminant digestive system. Since the GE is given in terms of dry matter (DM), the first stage of calculating a weighted average DE% is to calculate the DM makeup of the ration. Following this, the average DE is weighted based on the GE constituents of the ration (eq. 3.2).

Equation 3.2. Weighted average calculation for DE% in the ration.

$$DE\%_{ration} = \frac{\sum(DE\%_x \cdot Frac_x \cdot DM_x \cdot GE_x)}{\sum(Frac_x \cdot DM_x \cdot GE_x)}$$

Where:
$DE\%_{ration}$ = the DE% of the ration overall
DE_x = the DE% of ration component x
$Frac_x$ = the fresh weight (FW) fraction of component x in the ration
DM_x = the dry matter % of ration component x
GE_x = the GE (in MJ kg DM^{-1}) of ration component x

3.1.6. Accounting for changes in ration digestibility with season

Adding to the complexity of this approach is the non-linear relationship between DE% and enteric methane production (section 3.1.4). Whilst it is acceptable and biologically accurate to calculate the digestibility of the ration as shown in eq. 3.2, it is not possible to calculate averages between animal classes or time periods without incurring some inaccuracy in the modelled enteric methane emissions. For example, if two identical animals are raised on diets of 65% and 75% DE respectively, the resulting methane emissions would not be equivalent to a scenario where the same two animals were raised on diets of 70% DE; however, if the dietary DE values were averaged, this is what would be assumed. In practice, the inverse nature of the relationship means that averaging the two categories would result in an underestimation of the enteric methane production. The same rule applies where the same animal spends part of the year at pasture, and part of the year housed, as is the case in many northern hemisphere production systems (e.g. Casey & Holden, 2006). Where the grazed feed intake at pasture differs in digestibility to the ration fed whilst the animal is housed, it is important to account for the non-linearity in the modelled interaction.

Whilst emissions from individual livestock classes are treated and calculated separately in the model, this factor ensured that it was necessary to account for rations by class rather than as an overall average, necessitating the change in input structure described in section 3.1.5. However, model structure is such that it was not possible to account for enteric emissions from different time periods separately. To ensure emissions would be accurately captured for systems where this was the case, the approach of calculating a weighted average DE% was followed.

It was assumed, for simplicity, that livestock would experience a maximum of two distinct ration periods (summer grazing and winter housing) over the course of a year's production (though further changes e.g. store to finish can be accounted for through use of the different class definitions). This approach therefore weighted the calculated average of the DE between grass and pasture to reflect the non-linear nature of the interaction with enteric methane production. In other words, the calculated value does not represent a 'true' average ration digestibility, but rather weights this value to produce a modelled enteric methane estimate reflective of the change in DE% over time. The mathematical approach to this is shown in eq. 3.3.

Equation 3.3. Calculation of weighted DE% to reflect non-linearity of enteric methane relationship.

$$DE\%_{final} = 1/\sqrt{\left(T_{housed} \cdot DE\%_{housed}{}^{-2}\right) + \left(T_{pasture} \cdot DE\%_{pasture}{}^{-2}\right)}$$

Where:
$DE\%_{final}$ = weighted digestibility % of the overall diet
T_{housed} = time housed, as a fraction of the total year
$DE\%_{housed}$ = digestibility % of the housed ration
$T_{pasture}$ = time at pasture, as a fraction of the total year
$DE\%_{pasture}$ = digestibility % of the diet at pasture

The calculated $DE\%_{final}$ value was then used as an input for the IPCC Tier 2 calculations used to predict enteric methane emission (Dong et al., 2006). In order to quantify and assess the results of this change in approach, the following scenario was constructed:

Emissions were modelled for a 670kg suckler cow for one year. The animal was presumed to be producing a single calf, with a weaning period of 7 months (212 days). To simplify the estimate, the animal was assumed to be at pasture for 6 months, and housed for 6 months. The digestibility of the diet at pasture and housing were initially both set to 65%, and then varied in increments of 0.2% such that the average DE over the year remained the same, but the difference between the two situations increased. The final scenario had the housed ration digestibility 70%, and the pasture digestibility at 60% (Δ DE = 10%) (note: for this simulation, there was no difference in the two feeding situations other than the deliberate variation in DE% above; hence the same result would have been achieved with pasture at 70% DE and housed ration at 60%).

Enteric methane emissions, in kg CO_2-eq head^{-1} year^{-1} were then estimated for the modelled system, using a) an arithmetic mean DE%, and b) the approach described in eq. 3.3. Fig. 3.2 describes the relationship between the change in DE% and the discrepancy between a mean DE and DE weighted using eq. 3.3.

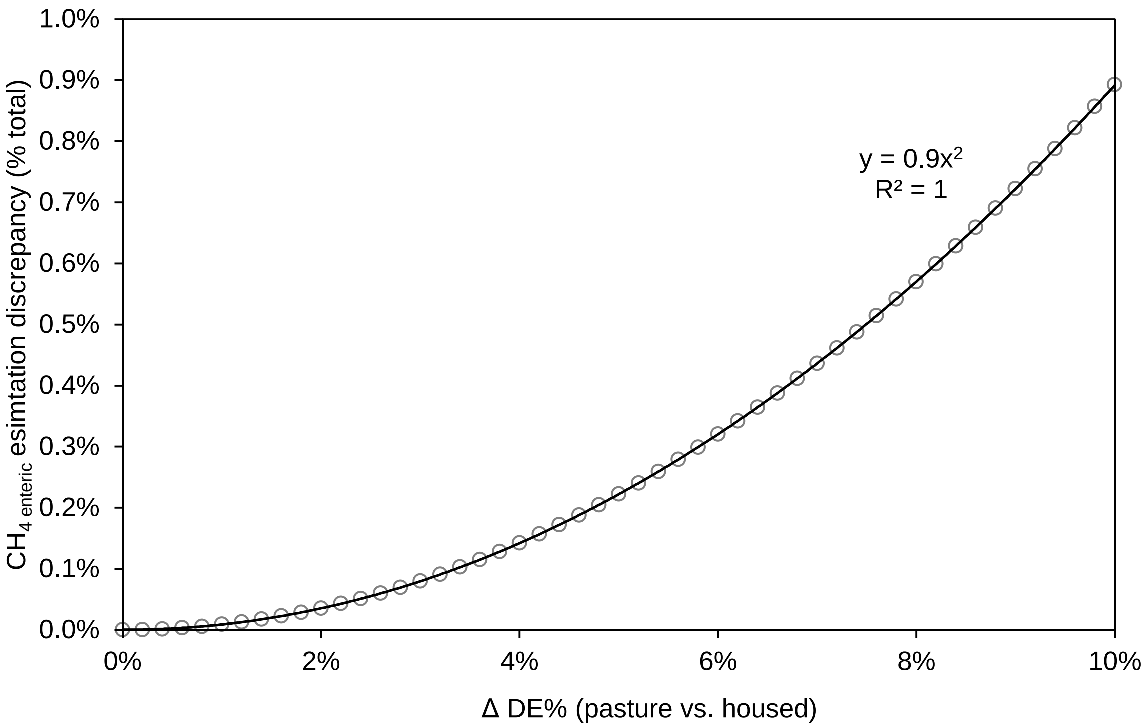

Fig. 3.2. The impact of a change in DE% between feeding situations (pasture/housed) on the discrepancy in estimated enteric methane generated by the assumption of a linear average DE for the full year. Plotted is linear average DE subtracted from DE calculated using eq. 3.3; hence, a positive value indicates an underestimation by the linear average approach.

The net result of using a linear average is a systematic underestimation of enteric emissions, which increases exponentially as Δ DE increases (Fig. 3.2). Based on the farm level data utilised in chapter two of this thesis, and published literature (e.g. Milne et al., 2014), ΔDE values of 5 – 10% are relatively commonplace, indicating that an unmodified approach would systematically underestimate enteric emissions by up to 0.9%. Whilst this underestimation is relatively small, it is significant given the magnitude of enteric emissions. It is also noteworthy in that any variation in dietary digestibility will yield an underestimation in enteric emissions if calculated using a linear average.

Chapter two reviewed four additional farm-level GHG footprinting tools. Notably, the Cool Farm Tool (Hillier et al., 2011) used a Tier 2 approach for livestock, but did not require input data necessary to make a distinction between housed and grazed rations; as such, it can be assumed that this systematic discrepancy is likely to be present in the estimates it generated. Other tools (the CALM tool, the CPLANv0 tool and the CFF calculator) followed simpler, Tier 1 approaches to modelling emissions from livestock, and as such, whilst less flexible, estimates generated with this approach are unlikely to have the same systematic bias.

3.1.7. Accounting for changes to DE% and CP% resulting from supplementary feed at pasture

Where rations are fed to housed cattle, calculation of digestible energy in the diet is relatively straightforward and can be completed as described in section 3.1.5. Similarly, when the animal is at grass, and if the entirety of the diet is comprised of grazed grass, calculation of DE for this period is effectively a case of taking a representative value for digestibility of pasture or rough grazing (following this approach, chapters five and six of this thesis are focused around modelling the digestibility of pasture).

However, the calculation becomes more complex where animals are supplemented at pasture. This approach is not infrequently utilised for higher-output grass-based systems (e.g. Casey & Holden, 2006). Since a large proportion of the diet is grazed rather than weighed and fed, the approach described by eq. 3.2 cannot be employed, since $Frac_x$ for the grazed portion of the diet is not known. This section describes the modelling approach used to solve this challenge.

The IPCC Tier 2 approach for calculation of emissions from enteric fermentation are based around an initial calculation of livestock gross energy requirements, based on weight, performance and activity levels (Dong et al., 2006). The relevant equation from this publication (10.16) was modified and implemented in the model secondarily to the calculation of enteric methane to calculate the overall digestible energy requirements (in kg hd^{-1} day^{-1} rather than as a percentage of gross energy) for each class during the period at pasture (eq. 3.4). Digestible energy was chosen rather than gross energy at this stage, since DE% forms a required parameter for the IPCC calculation of gross energy; clearly, overall DE% was unknown until the balance of pasture and supplementary feed was calculated.

Equation 3.4. Calculation of DE requirements for livestock class based on net energy requirements (adapted from Dong et al., 2006).

$$DE_{req} = \frac{NE_m + NE_a + NE_p + NE_l}{REM} + \frac{NE_g}{REG}$$

Where:
DE_{req} = animal digestible energy requirements (MJ hd^{-1} day^{-1})
NE_m = net energy required by the animal for maintenance (MJ hd^{-1} day^{-1})
NE_a = net energy for animal activity (MJ hd^{-1} day^{-1})
NE_l = net energy for lactation (MJ hd^{-1} day^{-1})
NE_p = net energy required for pregnancy (MJ hd^{-1} day^{-1})
NE_g = net energy needed for growth (MJ hd^{-1} day^{-1})

REM = ratio of net energy available in a diet for maintenance to digestible energy consumed (dimensionless)
REG = ratio of net energy available for growth in a diet to digestible energy consumed (dimensionless)
Note: for calculation of equation parameters from first principles, see Dong et al. (2006), eqs. 10.3 – 10.15.

It should be noted that in the approach specified by Dong et al. (2006), calculation of the equation parameters *REM* and *REG* requires use of a value for the DE% of the ration. Since this was unknown for the total ration, the digestibility of grazed grass was used as a substitute; this assumption was deemed acceptable given a) the likely similarity of pasture and supplementary ration DE%, b) the probability that this would form the majority of the ration at pasture and c) the low sensitivity of the overall calculation to *REG* and *REM*.

Having calculated overall digestible energy requirements per head for each class, eq. 3.5a was implemented to calculate the fraction of GE in the diet supplied by grazed grass, and eq. 3.5b to employ this value to allow a calculation of the DE% for the diet as a whole.

Equation 3.5a. Fraction of gross energy from grazed grass.

$$GE_{grazed} = \frac{DE_{req} - DE_{supp}}{\left(DE\%_{grazed}/100\right)}$$

Equation 3.5b. Overall DE% from pasture and supplementary feed.

$$DE\%_{pasture} = \left(\frac{DE_{req}}{GE_{grazed} + GE_{supp}}\right) \times 100$$

Where:
DE_{req} = modelled animal digestible energy requirements (MJ hd^{-1} day^{-1})
DE_{supp} = digestible energy supplied by supplementary feed, in (MJ hd^{-1} day^{-1})
$DE\%_{grazed}$ = digestibility of grazed grass, as a % of GE
GE_{grazed} = GE supplied by grazed grass (MJ)
GE_{supp} = GE supplied by supplementary feed (MJ)
$DE\%_{pasture}$ = the overall DE% of the diet at pasture, as a % of GE (final model input)

This approach effectively accounted for the unknown intake of grazed grass by animals at pasture, and allowed the calculation of dietary digestibility to be weighted accordingly. Supplementary feeding at pasture also has potential to impact the crude protein content of the diet, and so this approach was adapted to allow for calculation of this (eqs. 3.6a, 3.6b).

Equation 3.6a. Calculation of pasture dry matter intake.

$$DM_{grazed} = \frac{GE_{grazed}}{18.3}$$

Equation 3.6b. Combined crude protein percentage of grazed grass and supplementary feed.

$$CP\%_{pasture} = \left[\frac{(CP\%_{supp} \cdot DM_{supp}) + (CP\%_{grazed} \cdot DM_{grazed})}{DM_{supp} + DM_{grazed}}\right] \times 100$$

Where:
GE_{grazed} = GE supplied by grazed grass (MJ)
18.3 = gross energy density of grazed grass, in MJ kg DM^{-1} (Stergiadis et al., 2015)
DM_{grazed} = the DM intake from grazing, (kg)
DM_{sup} = the DM intake from supplementary feed (kg)
$CP\%_{grazed}$ = the CP% of grazed grass
$CP\%_{supp}$ = the CP% of supplementary feed
$CP\%_{pasture}$ = the CP% of the diet at pasture (final model input)

These approaches allowed for the dietary characteristics of a theoretically unlimited variety of production practices to be accounted for, based on minimal additional input data from the user.

3.2. Modelling embedded emissions for imported livestock feed

3.2.1. Rationale and background: embedded emissions from feed production

As discussed in section 3.1, a trade-off exists between enteric CH_4 produced by ruminant livestock, and N_2O and embedded emissions from feed production for ruminant systems (e.g. Pelletier et al., 2010; Hünerberg et al., 2014). In general, low-quality feeds require minimal inputs and hence have low associated emissions from production and application of agrochemicals; however, animals raised on these feeds exhibit poor performance and high enteric emissions. By contrast, high-quality feeds are more emissions-intensive to produce, but contribute to more efficient livestock production. This trade-off has been identified as a potentially influential determinant of the emissions intensity of beef production (section 1.4.3). Accurately characterising enteric CH_4 emissions, using an approach which specifically accounts for the quality of the fed ration, has been identified as a crucial element of this trade-off and has been considered in the previous section (3.1). The other element required to properly account for this interaction is to ensure that GHG emissions from the production of feed, both on- and off-farm, are adequately calculated.

3.2.2. Calculation of embedded emissions in AgRE Calc prior to development

Where crop production occurs on-farm, AgRE Calc requires the input of activity data relating to crop production; area, yield, agrochemical application rates, and so on. This data is typically available to the average user and represents sufficient detail to calculate a carbon footprint for production of the crop. AgRE Calc contains provision for the user to allocate crop production to any livestock production enterprise at class level, and as such emissions from production of feed crops are accounted for in the carbon footprint of livestock production. This approach was deemed adequate to account for on-farm feed production and was not modified.

Where livestock feed is produced off farm, prior to this stage, AgRE Calc made use of embedded emission factors for livestock feed calculated using the footprinting tool FeedPrint (Vellinga et al., 2013). This was an adequate approach in many respects, but had a number of inherent issues which rendered the investigation of an alternative approach expedient.

3.2.3. Updated approach to modelling embedded feed emissions

As identified in the introduction to this thesis (section 1.4.4), a primary aim of development of the AgRE Calc model was to facilitate the use of Monte Carlo methods to assess uncertainty and sensitivity in beef production LCA. Whilst the FeedPrint tool does in fact make use of a Monte Carlo approach to provide an estimate of uncertainty in the calculated emissions, there are a number of issues with this approach in the context of their use in AgRE Calc. Firstly, the scope differs considerably from that which could be assessed using AgRE Calc; namely, uncertainty in modelled N_2O emissions is not included in the FeedPrint assessment. Also, the Monte Carlo approach is simplistic; the number of repeats performed (N = 500) is low, limiting confidence in the calculated measure of uncertainty. As such, it was deemed appropriate to investigate methods of calculating embedded emissions which would not impose such restrictions on the use of Monte Carlo approaches in AgRE Calc.

Additionally, the way in which the FeedPrint tool performs the calculation of embedded emissions means that there is limited possibility to interrogate the footprint calculated for a particular feedstuff; whilst this feature did not pose an immediate barrier to its use in AgRE Calc, it did impose a restriction on the level to which the footprint could be analysed.

Finally, it also became clear based on the documentation of methodology used in FeedPrint (Vellinga et al., 2013) that there existed some differences in the scope employed by the FeedPrint model in comparison to AgRE Calc. Namely, these were the inclusion in the FeedPrint system boundaries of emissions from a) the production and maintenance of cultivation equipment, and b) emissions related to land use change (LUC). It is important to note that this was deemed to be an issue not because the validity of inclusion of these inputs in a carbon footprint is in dispute, but because the goal in this instance was consistency of approach. Were the FeedPrint emission factors to be used directly, assuming identical production practices and ignoring transport costs, the emissions associated with the production of, for example, one kilogram of wheat would be different than if modelled in AgRE Calc. As such, based on all of these factors, it was determined that an alternative approach to calculating embedded emissions from imported feed should be considered.

To this end, whilst the system boundaries of the FeedPrint tool were found to be inconsistent with the AgRE Calc approach, Vellinga et al. (2013) have ensured a good degree of transparency in the approach taken to the development of FeedPrint, enabling the activity data collated by the authors to be adapted to a methodology which is concurrent with the scope of AgRE Calc. It was therefore determined that the FeedPrint methodology documents should be employed as the primary source of activity data for crop production, and that a sub-model should be developed to calculate emissions based on this data for use in the AgRE Calc footprint.

The scope of this sub-model was designed to reflect that of AgRE Calc. Nitrous oxide emissions from crop residues, fertiliser application, and manure application were calculated, as in AgRE Calc, using emission factors from de Klein et al. (2006). Carbon dioxide emissions from lime and urea were calculated according to the same methodology. Emissions from electricity, fuel and agrochemical use were calculated using the same sources as AgRE Calc. Note that for electricity and agrochemicals, country of production impacts the choice of emission factor; this is of greater influence in production of imported feeds, which may be produced worldwide.

Activity data for crop production was sourced from the FeedPrint methodology reports for cereal production (Marinussen et al., 2012b), production of oil seeds (Marinussen et al., 2012d), and production of roughages (Marinussen et al., 2012c). Activity data from this source was also used for estimation of emissions from feed processing (Marinussen et al., 2012a; Marinussen et al., 2012e; Marinussen et al., 2012f).

3.3. Development of internationally applicable methodology in AgRE Calc

3.3.1. Direct methane emissions from livestock and manure

The methodology employed in AgRE Calc to calculate direct CH_4 emissions from livestock and manure (Dong et al., 2006) is designed to be internationally applicable. Many inputs to the calculation, such as livestock live weights, growth rates, ration composition, and so on are likely to change for different regions of production (e.g. Beauchemin et al., 2010 vs. Cardoso et al., 2016), but the core methodology of the approach is not specific to a particular geographic region. An exception to this rule is the methane conversion factor (MCF) for stored, deposited and spread manure, which varies with average annual temperature. The MCF for 10^{o}C was applied within AgRE Calc for simulations based in the United Kingdom, based on historic station data from the Met Office (2017). As an update, the full range of MCFs for the ranges 10−28^{o}C was included within AgRE Calc to provide flexibility for this factor. Given a) the potential for variability in this factor within even relatively small global regions, b) the relative simplicity of sourcing an estimate for this factor for a specific region and c) the relatively low impact of variability in manure methane emission on the overall footprint of most systems, it was decided that no further sample data should be sourced to aid in the selection of this coefficient, but that it should remain flexible to facilitate a variety of scenarios.

3.3.2. Direct nitrous oxide emissions from soils

As with the calculation of direct methane emissions, the IPCC guidelines methodology for the calculation of direct nitrous oxide emissions from soils (resulting from application of synthetic fertiliser, manure and other organic fertiliser, and crop residues remaining in the field) is designed to be internationally applicable (de Klein et al., 2006). Based on its application within AgRE Calc, no further updates were required to render this aspect of the AgRE Calc methodology valid for the simulation of scenarios outside of the United Kingdom.

3.3.3. Emissions from fuel and electricity

Method of electricity generation can have an important effect on the 'embedded' emissions within a kilowatt hour (kWh) of electricity usage. To reflect this within AgRE Calc, UK-specific data from DEFRA/DECC (2011) was replaced with a global dataset from GHG Protocol (2012). This allowed disaggregation of embedded emission from electricity to country level. By contrast, CO_2 emissions from on-farm burning of fossil hydrocarbons was not deemed to be region-specific; accounting for emissions from extraction of fossil fuels, this was deemed to be a) a relatively globally homogeneous process and b) difficult to pin to a specific region, with international trade of fossil fuels being widespread. As such, it was decided that the default DEFRA/DECC (2011) would be appropriate to employ for simulations based outside the United Kingdom. It is also worth noting that emissions from on-farm use of fuels and electricity typically form a relatively small part of the farm-level footprint (Sykes et al., 2017), and so, beyond a basic approach to capture the major international differences, intricate disaggregation of these based on global region is unlikely to greatly affect the calculated footprint.

3.3.4. Embedded emissions in agrochemicals and purchased livestock feed

Based on initial review of the literature, fertiliser production practices were found to be a) relatively variable between countries (Wood & Cowie, 2004) and b) potentially significant in terms of contribution to the overall farm-level footprint (see chapter two of this thesis; Sykes et al., 2017). As such, it was deemed expedient to attempt to characterise these differences for international scenarios modelled within AgRE Calc. Based on a review of published emission factors, data published by Kool et al. (2012) was selected based on the transparency of the methodology, and the international scope of the calculated factors. This approach also assisted with the Monte Carlo development described in section 3.4.

Emission factors for purchased livestock feed were modelled as described in section 3.2. These calculated emission factors, based on the activity data described (section 3.2) are geographically explicit and hence estimates can be deliberately targeted towards production practices in a certain area where appropriate. It is worth noting that some concentrate ration ingredients (e.g. soybean) are typically produced in a relatively small number of geographical regions, but may be exported to livestock systems worldwide. Properly accounting for this movement represents a challenge in the field of crop and livestock LCA, and warrants further investigation to improve estimates (Vellinga et al., 2013).

3.3.5. Further considerations in farm-level modelling with international scope

It may be more important to consider emissions associated with land use and land use change (LULUC) in developing nations where agricultural practices and areas are less defined. Given the issues associated with modelling emissions from this source, and the relatively fixed nature of agricultural practices and areas in the United Kingdom, AgRE Calc does not include this factor as an emissions source; however, in international scenarios this may be significant (Flysjö et al., 2012).

3.4. Development of Monte Carlo capability within AgRE Calc

Note: full record of the Monte Carlo parameters defined within AgRE Calc is presented in equations A.1 – A.4 and table A.3 (appendix). This section describes the rationale and methodological approach behind the process of developing Monte Carlo capability within the model.

3.4.1. Rationale and background: use of Monte Carlo simulation in GHG modelling for livestock systems

Several published studies (Gibbons et al., 2006; Lovett et al., 2008; Dudley et al., 2014; Zehetmeier et al., 2014) highlight the usefulness of Monte Carlo simulation in livestock LCA; these are discussed in introduction section 1.4.4. Chapter seven of this thesis also builds on and explores this approach. Additionally, the IPCC methodology used (as it was intended) for national inventory level calculations has been subjected to Monte Carlo-based sensitivity and uncertainty analysis by Milne et al. (2014) in the United Kingdom and Karimi-Zindashty et al. (2012) for Canada. Röös & Nylinder (2013) published a report summarising and discussing sources of uncertainty in livestock product carbon footprints.

Based on the results of these studies, it was determined that a critical development to AgRE Calc would be the optimisation of the model for Monte Carlo sensitivity analysis of uncertainty in modelled results.

3.4.2. Selection of Monte Carlo software

The version of AgRE Calc in use and development in this thesis was based in Microsoft Excel. MS Excel has limited ability to perform Monte Carlo simulations alone, but a number of add-in software packages are available to enhance this ability. Other software and languages (e.g. R, Matlab) are also capable of performing Monte Carlo simulations, but for ease of integration it was determined that AgRE Calc would remain Excel-based and an add-in package be employed. Identified packages were @Risk (Palisade Corporation), Crystal Ball (Oracle) and ModelRisk (Vose Software). Based on cost, usability and versatility, ModelRisk was selected to enable Monte Carlo simulations to be carried out directly within AgRE Calc.

3.4.3. Types of uncertainty a in farm-level tool

In a report on uncertainty in carbon footprinting of livestock products, Röös & Nylinder (2013) suggest breaking down the sources of uncertainty into three categories:

a) uncertainty or variability in input data,

b) uncertainty resulting from scenario choices such as scope and allocation method, and

c) uncertainty in modelling approach used to assess emissions from biological systems (epistemic uncertainty)

Uncertainty in input data (a) is of considerable importance in many livestock LCAs (Dudley et al., 2014), but characterising it in a farm-level tool such as AgRE Calc is problematic. In essence, the difference is that an LCA study has a fixed and defined purpose and scope, whilst a tool may be put to many different uses. The implication of this is that 'uncertainty' in input data may mean something very different depending on the intended use of the footprint; for example, a single, annual footprint may be used to estimate emissions for the farm for that particular year, or to provide an ongoing, non-temporally specific performance estimate. In each case, the input data for the footprint would be the same, but the associated uncertainties very different. With this in mind, it was determined that the tool itself would not attempt to deal with uncertainty in input data; this would be possible only if the user defined the scope and intended use of the footprint.

The second category defined by Röös & Nylinder (2013), in terms of scope and allocation method, is a valid concern in farm-level modelling. Chapter two of this thesis (published as Sykes et al., 2017) deals with this issue across a sample of farm-level tools. An assessment of model sensitivity to different approaches, together with logical justification of methodological choices is arguably the best approach to deal with this issue. Once issues of scope and allocation approach are defined, they are inherent in the model structure, and hence Monte Carlo simulation cannot be used to assess their impact.

It was therefore determined that the final category identified by Röös & Nylinder (2013) epistemic uncertainty, would be the focus of Monte Carlo optimisation of the AgRE Calc model. The approach would be 1) identification of Monte Carlo variables, i.e. modelling coefficients and emission factors which could be shown to exhibit epistemic uncertainty, 2) collection of data and definition of methodology to define the range and nature of uncertainties in these coefficients, and 3) integration of ModelRisk functions into AgRE Calc to allow characterisation of these variables using random samples drawn from modelled probability density functions (PDFs).

3.4.4. Identification of Monte Carlo variables

Any coefficient or emission factor employed within AgRE Calc is subject to epistemic uncertainty. The relative novelty of the approach meant that there was limited precedent to determine the most influential of these; additionally, the fact that a farm-level model such as AgRE Calc could be employed in a number of highly heterogeneous scenarios means that the influence of certain parameters could differ greatly depending on the scenario modelled. As such, it was determined that the approach to characterising epistemic uncertainty in these parameters should be as broad and inclusive as possible. The following categories of parameter were therefore defined as subject to uncertainty assessment within the model:

1) Coefficients used in the Tier 2 level livestock energy calculations (which provide a basis calculation of enteric CH_4, and CH_4 and N_2O from manure)
2) Coefficients used in the Tier 1 level calculation of crop residue available N
3) Coefficients used in the Tier 1 level calculation of direct and indirect N_2O emissions from managed soils (resulting from crop residues, application of synthetic N and application of manure or organic fertiliser)[9]
4) Coefficients used in the calculation of direct CO_2 emissions from application of lime and urea
5) Coefficients used in the calculation of emissions from the production of electricity used on-farm
6) Coefficients used in the calculation of direct CO_2 emissions from the burning of fossil fuels on-farm
7) Coefficients used in the calculation of emissions from the production of fertiliser and lime used on-farm
8) Coefficients associated with the application rate of pesticides used on-farm
9) Coefficients used in the calculation of emissions from the production of herbicides, insecticides and fungicides used on-farm
10) Coefficients associated with the dry matter (DM), gross energy (GE), digestible energy (DE) and crude protein (CP) content of livestock rations (factors which contribute to the Tier 2 level calculation of enteric CH_4, and CH_4 and N_2O from manure)
11) Coefficients used in the calculation of emissions from imported livestock feed and bedding

This approach was intended to provide a comprehensive overview of epistemic uncertainty within the calculation of scenarios in AgRE Calc; no source of uncertainty was knowingly omitted from this inventory.

[9] It should be noted that, reflective of high uncertainty in the IPCC methodology, the United Kingdom has recently developed Tier 2-level N_2O EFs for agriculture (Chadwick et al., 2016). These were not available during the development of AgRE Calc as described in this thesis.

3.4.5. Data collection and methodology for Monte Carlo variables

Identification of data sources and definition of the methodology required to characterise uncertainty within AgRE Calc formed the majority of the effort required to carry out this process. This section discusses data identification and manipulation under the categories defined in section 4.4.

3.4.5.1. Uncertainty in IPCC Guidelines calculations (cats. 1 – 4)

Data for uncertainty sources 1), 2), 3) and 4) was sourced from within the IPCC (2006) Guidelines for National Greenhouse Gas Inventories. The IPCC recommend that countries reporting under the methodology quantify and report the uncertainty associated with the estimates, and whilst the methods for achieving this are not necessarily clear-cut (Milne et al., 2014), the chapters relevant to AgRE Calc (Dong et al., 2006; de Klein et al., 2006) nonetheless provide estimates of uncertainty in the key calculation parameters. These were used to define Monte Carlo variables for these calculations.

Data from Dong et al. (2006) was used to quantify uncertainty in the Tier 2 level energy calculations for livestock. This data typically took the form of best, minimum and maximum estimates. Where these distributions were not skewed around the best estimate, it was deemed appropriate to employ a normal (Gaussian) distribution to characterise these coefficients. The key interpretive factor in this process was the definition of unbounded distributions from bounded estimates; Milne et al. (2014) also followed this approach (though using data from Penman et al., 2000), and chose to interpret the min-max range as a 95% CI to allow the use of an unbounded distribution. The same approach was followed here.

Regression equations are defined in de Klein et al. (2006) for the crop-specific calculation of N remaining in crop residues. Broadly, these equations predict remaining above-ground residue biomass following crop removal. These are then related to total above-and-below-ground biomass and subsequently to total remaining nitrogen. Uncertain parameters in this calculation (as defined by de Klein et al., 2006) are the slopes and intercepts of the regression equations, and the ratio of above ground to below ground biomass. Standard deviations are defined by the authors for these variables, and together with the mean estimates these were used to parameterise normal distributions for each crop type. Dry matter (DM) content of residues is also an important scaling factor in this calculation; no uncertainty estimates were provided for this by de Klein et al. (2006), but given the potential variability of this factor, it was determined that this should be included in the uncertainty assessment. The characterisation of this factor is discussed under section 3.4.5.4.

Uncertainties for emission of N_2O and CO_2 from soils were characterised using data from de Klein et al. (2006). All N_2O emission factors show a positive (right-tailed) skew. This reflects the pattern typically observed in measurement of N_2O emissions (e.g. Rees et al., 2012). Previously, some authors (e.g. Milne et al., 2014) have chosen to characterise this using a lognormal distribution, whilst others (e.g. Gibbons et al., 2006) have used triangular distributions.

Uncertainty statistics were presented for N_2O in the form of a best estimate with minimum and maximum bounds (de Klein et al., 2006; Dong et al., 2006). Whilst the triangular distribution is more straightforward to parameterise with these data, the increased weight this type of probability density function (PDF) puts on the distribution 'tails' can lead to under-representation of the best estimate in the Monte Carlo analysis, and subsequently to systematic bias where the distributions are skewed. It was therefore decided to follow the approach of Milne et al. (2014) and to utilise a lognormal distribution to represent uncertainty associated with nitrous oxide emission factors.

The IPCC methodology for the calculation of N_2O emissions from soils and manure systems also include other coefficients, in addition to the emission factors themselves. These coefficients are associated with the processes leading to the indirect emission of N_2O (namely volatilisation and leaching) and denote the fractions of N from a particular pool which are transported by these processes (Dong et al., 2006; de Klein et al., 2006).

Uncertainty statistics are presented for these coefficients in the form of a best estimate and range, as above. However, there is no theoretical justification for reconciling these values to a lognormal distribution. Skew is also variable between coefficients, suggesting that a normal distribution would be inappropriate. Milne et al. (2014) applied a Beta distribution to these coefficients, and a similar approach was chosen here.

The PERT distribution (also called Beta PERT) is a derivative of the Beta distribution, and is designed specifically for the purpose of modelling expert estimates (Clark, 1962). As such, it follows the basic format of a Beta distribution, but employs a best, minimum and maximum estimate as distribution parameters. It was chosen for this purpose as it represents an advantage over the simpler triangular distribution through lower weighting of the distribution 'tails', and hence lower likelihood of systematic error where distributions are skewed. A PERT distribution was also deemed most appropriate for EFs denoting CO_2 emissions as a fraction of applied lime and urea.

3.4.5.2. Uncertainty in emissions from fuel and electricity (cats. 5 & 6)

For emissions from electricity production, AgRE Calc makes use of emission factors provided by GHG Protocol (2012). These EFs are geographically specific, varying to reflect differing electricity generation practices by country. This database does not provide a *de facto* estimate of uncertainty in the emission factors provided, so the range of values given for emission factors from 2000−2012 was employed to provide an estimate of variability. No consistent temporal trends were identified in the factors. A Beta PERT was therefore employed to characterise uncertainty in electricity production, with the best estimate (BE) corresponding to the most recent (2012) emission factor, and the minimum and maximum value reflecting the range across the sampled time period.

For emissions from diesel use, a similar approach was followed, utilising EFs from the DEFRA/DECC Conversion Factors for Company Reporting. For the best estimate, the 2015 EF was utilised, with uncertainty stemming from the range 2012−2015. As with electricity EFs, an Beta PERT distribution was employed, with the BE reflecting the most recent factor.

3.4.5.3. Uncertainty in agrochemical emission factors (cats. 7 – 9)

Prior to the development of Monte Carlo capabilities in AgRE Calc, emission factors for synthetic fertiliser used on farm were sourced from the EcoInvent emission factor database (Ecoinvent Centre, 2007). There were a number of issues inherent in this approach; namely a) as 2007 values the EFs risked becoming outdated as practices progress, b) the supplied EFs were not specific to fertiliser types, but rather generalised estimates for N, P and K nutrients, and c) the EFs were UK specific and could not be validly applied abroad (see also section 3.3). In addition to this, no *de facto* uncertainty estimates were supplied with the EFs, limiting the extent to which confidence in the resulting calculations could be assessed.

Data published by Kool et al. (2012) provided the solution to this issue. The EFs derived by these authors were geographically explicit, product specific and were presented alongside estimates of confidence/variability. Skew in these estimates was variable in direction; as such, a Beta PERT distribution was chosen to characterise emission factors specific to the following categories:

- **World region:** Western Europe, Russia/central Europe, North America, China/India, and Rest of World
- **Product type:** Urea, liquid UAN, anhydrous ammonia, ammonium nitrate, CAN, ammonium sulphate, MAP, DAP, NPK (based on AN, AP and MOP), NPK (based on Urea, TSP and MOP), NK (based on nitric acid and MOP), triple super phosphate, single super phosphate, ground rock, PK, potassium chloride, potassium sulphate, and lime

In addition to the geographically- and product-specific categories, additional distributions were specified to represent non-specific iterations of each category (i.e. world average factors and non-product specific factors) based on data from Kool et al. (2012).

Replacing the EcoInvent EFs (Ecoinvent Centre, 2007), AgRE Calc was updated to employ emission factors calculated from data provided by Audsley et al. (2014). The reasons for this were a) the potential for the EcoInvent data to become outdated, and b) the potential for calculation of uncertainty in the estimated values. Audsley et al. (2014) provide a raw dataset of estimates for emissions associated with the production of different types of herbicide, insecticide and fungicide. Since the input data in AgRE Calc is non-product-specific, variability in product type was deemed to be a source of epistemic uncertainty. There is also likely to be another layer of epistemic uncertainty associated with the production of individual pesticide types; data was not provided for this, but it was believed that this would be relatively minor in comparison to uncertainty in product type, and would be effectively ‘eclipsed’ by this uncertainty source.

The datasets provided by Audsley et al. (2014) were relatively small (N = 37, 10 and 22 for herbicides, insecticides and fungicides respectively). As such, it was not advisable to infer complex distribution shapes from these datasets; examination of the data spread did not indicate a tendency towards skew and suggested a relatively uniformly distributed dataset. As such, a uniform distribution was used to characterise uncertainty in the pesticide production EFs, with the range of each dataset used to parameterise the distribution. PDFs for production of herbicides, insecticides, fungicides, and (utilising the entire dataset, $N = 69$) of an 'average' pesticide.

AgRE Calc also provides the opportunity for users to employ fixed, crop-specific application rates for pesticides. These are based on data published in a number of reports on application rates for different sectors of production in the United Kingdom, namely arable crops (Garthwaite et al., 2012a), grassland and forage (Garthwaite et al., 2013a), vegetable crops (Garthwaite et al., 2013b) and soft fruit (Garthwaite et al., 2012b). Given the legislation which surrounds the application of pesticides, these application rates are relatively specific, but nonetheless an element of variability is present in the estimated value. The authors provide an estimate of this variability, and this was treated as epistemic uncertainty in the model. A uniform distribution was applied to each crop-specific application rate.

3.4.5.4. Uncertainty in crop and livestock ration characterisation (cat. 10)

Dry matter (DM, % of fresh weight), gross energy (GE, MJ kg DM^{-1}), digestible energy (DE, % of GE) and crude protein (CP, % of DM) in the ration are required inputs for AgRE Calc. DM is required for livestock feed to allocate DE and CP calculations (see section 3.1) and, for home-grown crops, to calculate crop residue N content. GE, CP and DE are direct inputs for the IPCC Tier 2 calculation of enteric methane, manure methane, and manure nitrous oxide (Dong et al., 2006). Digestible energy directly impacts enteric CH_4 emissions and manure production quantity (which in turn impacts emissions of manure CH_4 and N_2O); dietary CP% scales manure nitrogen content, which directly scales N_2O emissions. Dietary DE% and CP% are calculated in AgRE Calc as described in section 3.1; this section describes the characterisation of uncertainty in this process.

Feedipedia (INRA, 2012) was used to supply estimates of the standard deviation for the DE% and CP% of fed rations by individual ration component. Standard deviations were also sourced for the gross energy (GE) and dry matter (DM) content, also used in the calculation of dietary characteristics for the fed ration (see section 3.1). For grazed grass, the model developed and described in chapters five and six of this thesis was used to provide an estimate of standard deviation for DE% and CP%; this model was intended to be used in conjunction with AgRE Calc, but for basic functionality, a constrained run of this model with estimated median parameters N_{rate} = 125 kg ha^{-1} $year^{-1}$ and S_{age} = 7 years (see chapter five for greater detail) was used to provide a baseline estimate of DE/CP% and associated uncertainty. There was no evidence to suggest that skew existed in any of the dietary parameters, and so a normal distribution was employed to characterise these. The DE, CP and DM parameters are employed in the modelling process as percentages (DE as a % of GE, CP as a % of DM, DM as a % of fresh weight) and so the distributions were bounded at 0 and 100% to ensure stochastically sampled values would remain within this boundary.

3.4.5.5. Uncertainty in embedded emissions in feed production

No adequate database characterising uncertainty in emissions from livestock feed production could be found for the purposes of this study. It was therefore determined that emissions from imported livestock feed should be calculated *de novo*, allowing the assessment of uncertainty in results to be made as part of this process. Section 3.2 describes this process in detail; this section describes the characterisation of uncertainty in this process.

All IPCC-based calculations were subject to the uncertainties defined in section 3.4.5.1. Electricity and fuel use uncertainties followed the approach defined in 3.4.2.2., and uncertainty in emissions from application of agrochemicals followed the emission factors defined in 4.2.3. Uncertainty in emissions from the processing phase of processed feeds was also considered, and electricity and fuel use uncertainties, as already characterised, were employed here. The activity data published alongside the FeedPrint tool, used for the characterisation of production practices (see section 3.2), was also used to provide estimates of uncertainty in key production parameters, namely:

a) yield
b) agrochemical application rates
c) organic fertiliser application rates
d) processing energy requirements

In gathering and presenting the activity data in this way, the FeedPrint developers had intended its use in Monte Carlo simulation, and as such there was little interpretation required for its adaptation to AgRE Calc. Distributions applied were variously normal, lognormal and uniform, and were applied according to recommended practice by Vellinga et al. (2013).

3.4.6. Integration of approach within AgRE Calc

The first stage of the integration of this approach into the Excel-based AgRE Calc model was to generate a master spreadsheet into which the defined PDFs could be collated (this collated dataset is summarised in table A.3). ModelRisk (Vose Software) allows the characterisation of probability mass functions (PMFs) and probability density functions (PDFs) using Excel formulae. These formulae utilise Excel's base function pseudo-random number generator to stochastically sample from the mathematically defined PDF or PMF. In effect, the computer is then able to sample randomly from within the defined function, and the output changes accordingly each time the spreadsheet is recalculated. The equations for these functions are noted in appendix section A.2 (equations A.1 – A.4).

Whilst being a fully necessary part of the Monte Carlo simulation framework, this in itself presented a number of challenges. Firstly, with computed values changing with each spreadsheet recalculation, it rendered the model itself more difficult to work with; with the model calculating stochastically, it was impossible to check with certainty which coefficients were being employed in each calculation, and how. Secondly, there were 938 PDFs (2,378 parameters) defined under the categories described in section 3.4.5; sampling from such a large number of stochastic formulae served to impose an unnecessarily high computational load on the system, both during normal use of the model and during a Monte Carlo simulation. Finally, with an excessively large number of stochastic variables, the ability of the user to interrogate the results of the Monte Carlo simulation would be substantially hindered. As such, it was deemed necessary to develop a system which would allow the activation of only those variables which would have an impact on the specific calculation being conducted (for example, if a modelled scenario contained wheat, but not barley, as a livestock feed, it would be advantageous if the resulting Monte Carlo simulation accounted for stochastic variables relating to wheat, but omitted those relating to barley). Such a situation would be possible to create manually, but would be a) highly labour intensive and b) require a high level of knowledge relating to the propagation of uncertainty through the model.

The first step in this approach was to bracket each stochastic variable with a logical operator (an [=IF()] function) to enable it to be activated only when required, with the addition of a 1 in an adjacent 'operator' cell. With the operator cell set to 0, the stochastic coefficient would revert to its deterministic value and the model (with respect to that coefficient) would calculate normally. Following this, a script was written in MS Visual Basic for Applications (VBA) which would automate a sensitivity testing process for each individual variable. A lay summary of this script is presented below:

1. Set all coefficient to deterministic values
2. Record total modelled GHG emissions for system as [Output 1]
3. Activate first stochastic coefficient [Coefficient 1]
4. Recalculate model
5. Record total modelled GHG emissions for system as [Output 2] *
6. If [Output 1] = [Output 2] then mark [Coefficient 1] as inactive
7. If [Output 1] ≠ [Output 2] then mark [Coefficient 1] as active
8. Deactivate [Coefficient 1]
9. Move to next coefficient and repeat from step 4.

*In that this element of the code makes use of pseudo-random processes it is technically possible that the stochastically modelled value could be the same as the deterministic value. However, Excel calculates random variables to 16 decimal places, meaning the probability of this occurring is so small as to be negligible.

Following this process, the user is provided with a list of strategically tested 'active' coefficients (coefficients which impact the model results) which can be a) activated, as desired, and b) included as inputs in the Monte Carlo simulation. Including such a coefficient as a Monte Carlo input enables ModelRisk to track and record it in the same way as an output variable, and also to apply it to sensitivity analyses. As such, the stochastic variables defined theoretically in section 3.4.5 are integrated into the existing model and add Monte Carlo capability to address the issue of epistemic uncertainty in the calculation of GHG emissions as modelled at farm level.

Chapter seven of this thesis provides a full exploration of the impacts of epistemic uncertainty in a beef production system modelled at farm level, utilising the approaches and framework defined in this section.

Chapter Four

The carbon footprint of beef finishing systems – results from a lifetime experiment

4.1. Introduction and Rationale

4.1.1. Beef system life cycle assessment as a tool for greenhouse gas mitigation

Life cycle assessment (LCA) methodology is an important tool in understanding and quantifying impacts from complex systems such as livestock production (Opio et al., 2013). As a result, many LCA studies globally have focused around beef production, with the aim of better understanding greenhouse gas (GHG) emission patterns and identifying opportunities for mitigation. In following a whole-system approach, the aim is generally to identify emissions hotspots as ‘low-hanging fruit’ for mitigation effort, and to highlight areas where production efficiency can be improved. A whole-system approach is necessary to avoid false economies in mitigation, whereby one emissions source is traded for another (Janzen et al., 2006), and to provide deeper understanding of process flows within the system. The complexity of these systems represents one of the main obstacles to mitigating emissions from beef production, with issues stemming from a) variation and uncertainty surrounding the effect of production practices on the footprint, which is exacerbated by regional variability (Opio et al., 2013), and b) limitations in the ability of LCA studies to accurately capture the intricacies of this variation and its impacts.

The LCA literature has identified several factors which have a key impact on the emissions intensity of production; the duration of the finishing period is one such variable. The lifetime of a beef animal typically scales strongly with its overall carbon footprint, but this increase in emissions is offset by live weight gain, and so the emissions intensity of production does not follow such a clear pattern. Regional and local variation in conditions and practices means an optimum value for this is elusive. Pelletier et al. (2010), comparing a range of production strategies in the US mid-west, found that feedlot finishing represented the most efficient strategy from the perspective of GHG emissions. In general, shorter finishes were found to represent better efficiency, whilst longer, slower-growth finishes produced more emissions per kg of beef produced. Casey and Holden (2006), in assessing suckler beef production in Ireland, also found that shorter finishes typically represented better efficiency. However, holistic approaches have also suggested that slow-growth, low-input systems may represent greater emissions efficiency in comparison to more intensive approaches (Subak, 1999).

Cardoso et al. (2016), assessing intensification of beef production systems in Brazil, found that whilst increasing levels of intensification typically reduced the emissions intensity of production, there were exceptions to this direction, and the reduction in emissions became less marked with progressive levels of intensification.

In addition, the diet of beef cattle is shown to represent an important factor in the carbon footprint (Beauchemin et al., 2008). This may be particularly instrumental in the case of a beef finishing system (Pelletier et al., 2010; Beauchemin et al., 2010). Replacement of roughage with concentrate in the ration of finishing animals reduces enteric CH_4 through lowering ruminal pH, and replacing fibre with starch in the fermented substrate. However, production of concentrate feed is emissions intensive, and so a trade-off between enteric CH_4 and land-based emissions of N_2O (with the latter produced either on-farm or elsewhere) may result (Hünerberg et al., 2014). As such, the abatement potential of increased dietary supplementation is dependent on the interactions between production of enteric CH_4, rates of live weight gain, and emissions generated in the production, processing and transport of the concentrate ingredients. The trade-off is therefore complex; the direction and magnitude of the overall response can be both positive and negative, and can vary considerably between scenarios (Beauchemin et al., 2008). This leads to uncertainty in the most efficient approach to raising and finishing beef cattle, and the assumptions employed in a study can lead to conclusions favouring high-input approaches (e.g. Pelletier et al., 2010) or extensive, low-input systems (e.g. Subak, 1999). As such, variation in assumptions from different modelling approaches compounds uncertainty from real-world variability.

4.1.2. Challenges in LCA

Capturing interactions between different aspects of a complex system is a challenge for LCA practitioners; in most case study-type LCA studies, data collected from industry or farm-level sources is relied upon as the basis for calculation (e.g. Beauchemin et al., 2010; Dudley et al., 2014). However, particularly where a study seeks to make comparison between approaches, the scenarios modelled are often partly or entirely hypothetical (e.g. Pelletier et al., 2010). Whilst in many respects this represents a strength of the LCA approach, it also means it is frequently necessary for the authors to hypothesise the values of scenario variables. Variation in (and interaction between) certain variables can have considerable impact on the modelled footprint (Dudley et al., 2014; see also chapter seven of this thesis), which may account for some of the disparities in the conclusions drawn from the LCA studies discussed thus far. Partly in response to this there is a recognised requirement for improved accuracy, requiring more detailed approaches, in modelling livestock emissions (Caro et al., 2016; Sykes et al., 2017; see chapter two of this thesis). However, increased complexity typically requires either greater detail in input data, or increasing reliance on assumptions; the latter may serve to negate the advantage of a more complex approach.

Further to this, LCA studies are typically performed at the system level, meaning a point estimate is generated for the emissions intensity of a single system. It is therefore typically not possible to statistically compare systems or system types, and so an estimate of confidence in the results of a comparison becomes difficult. Sensitivity analysis, often performed via Monte Carlo simulation to model uncertainty, may address this to some extent (e.g. Monni et al., 2007; Dudley et al., 2014), though accurate characterisation of variable uncertainties is important if this approach is to yield useful results (chapter seven of this thesis explores this further). Decreasing the granularity of estimates could facilitate statistical insight into comparisons between scenarios, but such an approach would be reliant on far more detailed input data than is typically available.

Further exemplifying the complexity of beef production systems, many systems globally are highly seasonal, particularly in northern hemisphere, temperate areas (Opio et al., 2013). Animals may be housed for part of the year, typically during colder or wetter seasons (e.g. Casey and Holden, 2006; Beauchemin et al., 2010). This is distinct from housing or confining to yards for the sole purpose of controlling dietary intake, which is common practice for feedlot-based systems (Pelletier et al., 2010). Nevertheless, seasonal movement between housed and grass-based situations represents a distinct change in diet and activity levels, and many affect animal performance accordingly (section 3.1 of this thesis considers in detail the modelling implications of this). All of these factors directly impact the carbon footprint of production. However, in the available LCA literature, there is a dearth of studies which examine seasonal differences in emissions from such systems. For reasons already discussed, many studies rely on assumptions or broad estimates for variables relating to animal rations and performance, and this breadth may prohibit more detailed dissection of the footprint. The lack of consensus surrounding the optimal approach to production may be in part related to the temporal granularity of typical LCA studies; as such, further dissecting the footprint into shorter, internally consistent periods may yield some insight into differences between systems.

4.1.3. Aims and objectives

In the context of the global effort to reduce emissions from the beef production sector, this study aimed to address some of these challenges currently faced by LCA researchers. Additionally, this study sought to further explore some of the factors, such as finish duration, type and diet, which have been identified as important determinants of emissions intensity. As such, this study aimed to provide an LCA-based assessment of beef finishing systems in the United Kingdom, with an emphasis on identifying key features which contribute to emissions savings. To minimise reliance on assumptions for key variables in the modelled finishing system, this approach made use of performance data collected as part of a lifetime experiment on finishing beef cattle, with an aim to substantially reduce uncertainty surrounding interactions between feed production, ration consumption, and animal performance variables. Data collected from this experiment provided a basis for comparison of different durations and types of finish, providing insight into the current differential findings in this area. Key dietary and performance parameters were measured at the level of the individual animal, and carbon footprinting was carried out at this level; as a result, the carbon footprint results for each finish type formed a statistically comparable dataset.

The temporal granularity of the footprint was also reduced through regular collection of performance data, allowing footprinting to be carried out for separate seasons of the finish. This allowed comparison to be made between summer and winter footprints for animals moving between housed and grazing situations. Finally, in order to provide context for the finishing footprints, two simulated parent systems were modelled for the finishing animals. These systems aimed to represent a) a typical UK suckler beef system and b) a typical UK dairy system, supplying dairy-bred beef finishing animals. To overcome to the greatest extent possible issues associated with the impact of assumptions (Dudley et al., 2014), Monte Carlo simulation was used to model uncertainty and variability present in the system data. These systems were designed to provide context to the more detailed analysis of the finishing systems, and to form the basis for assessment of the potential of the beef finishing system to impact the overall emissions intensity of production.

4.2. Methodology

4.2.1. Finishing system experiment

This section describes the formulation of a controlled experiment designed to form the basis for a comparison of beef finishing systems. This lifetime experiment was conducted by the IBERS department of Aberystwyth University, at Gogerddan research farm in West Wales[10]. It was designed primarily with the aim of providing a basis for the assessment of eating quality and shelf life of beef, though also collected data for the purposes of carbon footprinting.

One hundred and eighty Angus-Holstein steers were transferred at two weeks of age to a standardised rearing unit. The steers were weaned and reared on a standardised diet, and based on consistency in live weight, health and condition score, 132 animals were selected to take part in the lifetime experiment following weighing and condition scoring at between 8 and 12 weeks of age. These animals were then balanced between six different finishing treatments, broadly defined as:

a) high quality grass-based
b) medium quality-grass based
c) short period slow-growth followed by fast-growth final finish
d) long period slow-growth finish
e) concentrate based (high vit. E)[11]
f) concentrate based (low vit. E)[2]

[10] Note that this experiment was designed and conducted entirely by research staff at Aberystwyth University (see thesis Acknowledgements). Data from the experiment was supplied to the author for the purposes of the analyses reported herein.
[11] Variation in dietary vitamin E has been shown to impact beef shelf life (Gray et al., 1996), and diets E and F were formulated to assess this hypothesis as part of a separate study.

Even division of the experimental group (N = 132) led to group sizes of 22 animals per treatment. Aside from variations in diet, the six finishing systems also varied considerably in terms of duration and housing strategy (Fig. 4.1).

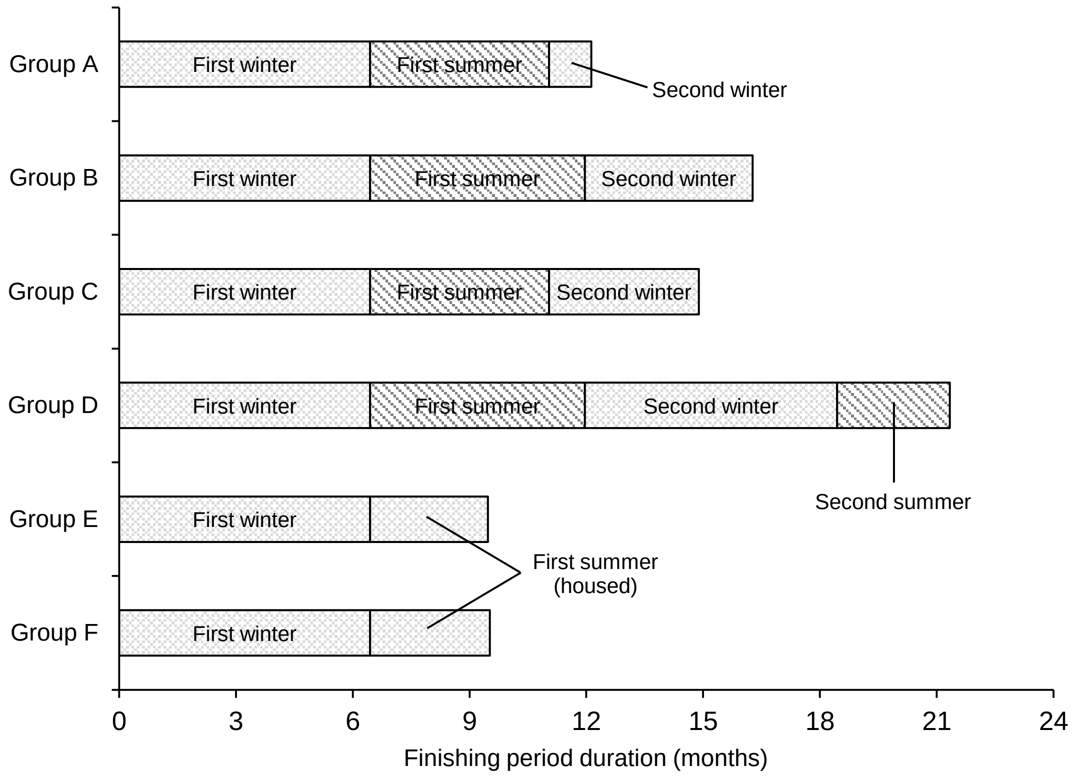

Fig. 4.1. Duration and housing regime for the six finishing systems. Unless otherwise specified, animals were housed for the winter period and at grass during the summer period.

Diets for the groups and finishing periods were specified in accordance with live weight gain (LWG) targets (table 4.1). For groups A-D, no concentrates were specified, though LWG was prioritised in the finishing period such that groups A-C had provision for concentrate supplementation during the housing period where it was necessary to maintain growth paths.

Table 4.1. Projected dietary composition and target LWGs (shown square brackets, in kg hd^{-1} day^{-1}) for the six groups across the finishing period. Note that these figures/dietary composition are targets; achieved LWG and corresponding diets are presented in results (section 4.3.1).

	First winter	First summer	Second winter	Second summer
Group A	Silage/straw/ minerals [1.1]	Grazing [1.1]	Silage/straw/ minerals [1.1]	
Group B	Silage/straw/ minerals [0.8]	Grazing [0.8]	Silage/straw/ minerals [0.8]	
Group C	Silage/straw/ minerals [0.5]	Grazing [1.1]	Silage/straw/ minerals [1.1]	
Group D	Silage/straw/ minerals [0.5]	Grazing [0.5]	Silage/straw/ minerals [1.1]	Grazing [1.1]
Group E	Concentrates/straw [1.1]	Concentrates/straw [1.1]		
Group F	Concentrates/straw [1.1]	Concentrates/straw [1.1]		

Silage and grazing were supplied by high quality sugar grass and ryegrass swards on site at Gogerddan farm. Barley straw, concentrates and minerals were purchased from external suppliers. The land used for grazing and silage was treated with 25−5−5 NPK fertiliser based on ammonium nitrate, triple superphosphate and muriate of potash, applied at an overall rate of 740 kg ha^{-1}. No lime, pesticides or other agrochemicals were used.

The animals were fed using a combination of Hoko feeders and ad-lib feed bins. Live weights for each individual animal were recorded at purchase and slaughter, and at the beginning and end of each period defined in table 4.1.

4.2.2. Modelling approach

As data on individual animal weight and feed intake was available, it was possible to conduct the footprinting process at the level of the individual animal. Additionally, given the frequency with which animals were weighed and feed intakes recorded, it was determined that separate footprints should be calculated for each of the individual feeding periods defined in table 4.1.

The farm-level footprinting model AgRE Calc (SRUC, 2014) was used to provide a footprint estimate. Full details of model functionality are described in Sykes et al. (2017) (chapter two of this thesis); only details specific to this study are summarised here. For the grazing period, a cage system was employed to estimate grass growth, and dry matter (DM) removals were estimated according to the methods described by Lantinga (1985). Gogerddan farm employed a rotational grazing system for the finishing cattle in this group; cattle were rotated between 12 separate plots throughout the course of the finish.

The majority (10 of 12) of the plots were reseeded on a 7-year rotation, while the remainder (2 of 12) were on a 20-year rotation. Plots also varied in size, so emissions from the renovation process (N_2O from crop residues) were allocated per plot to individual groups on the basis of calculated DM removals by each group on each rotation.

Grass digestible organic matter (OMD) and crude protein (both in g kg DM^{-1}) for each plot were measured directly in laboratory analyses. The crude protein fraction of dry matter is a required modelling input (Dong et al., 2006) and was directly utilised; grass OMD was converted to DE% (digestible energy as a percentage of gross energy, a modelling input), using a regression equation developed by Rittenhouse et al. (1971).

Emissions from production of feed concentrates were estimated based on compositions provided by the supplier, Mole Valley Feeds. Five different types were utilised in the production system. The ingredients were provided in order of relative volume, but given that feed formulae are proprietary and deemed commercially sensitive, exact quantities were not supplied. To overcome this, concentrate proportions were defined as uniform random variables, with magnitudes defined by the known relative volume order (eq. 4.1) in order that Monte Carlo simulation could be used to account for the uncertainty and provide the production emissions estimate.

Equation 4.1. Structure of random variables representing relative ingredient proportion for concentrate feed.

$$1 \geq x_1 \geq x_2 \geq x_{3\,etc.} \geq 0$$

Where x_1, x_2, x_3 are relative proportions of concentrate ingredients 1, 2, 3 etc.

Concentrate main ingredients comprised barley, wheat, rape meal, sugar beet pulp, maize, sugar cane molasses and oats. Emission factors for the raw ingredients, together with emissions from processing and transport were calculated according to methods and activity data documented by Vellinga et al. (2013) and van Zeist et al. (2012). Metabolisable energy (ME, in MJ kg DM^{-1}) and crude protein content (as % of DM) were estimated for each concentrate type based on laboratory analysis. The ratio of ME to DE is relatively constant, and so ME was converted to DE (in MJ kg DM^{-1}) using a conversion factor of 1/0.82 (ILCA, 1990). To calculate DE as a percentage of GE (the required modelling input), the gross energy content of individual ingredients was also calculated based on data from Feedipedia (INRA, 2012) and van Zeist et al. (2012).

A Monte Carlo simulation of 10,000 repeats was used to provide an estimated mean weighting for the concentrate composition, enabling calculation of a weighted emission factor and GE content for each concentrate type. Digestible energy as a percentage of GE was subsequently calculated from this value and utilised as a model input. The only other purchased feed used in the finishing systems was barley straw; emissions from this feed were calculated according to Marinussen et al. (2012), and existing the existing nutritional database from AgRE Calc (originally sourced from INRA, 2012) was used to characterise DE% and CP%.

Simulations were run in AgRE Calc to estimate GHG emissions for each individual animal and feeding period. Manure was stored in deep bedding for the housed periods; it was assumed that this was allocated to a cropping enterprise following storage, so the finishing animals were allocated only the emissions from manure storage. Pasture and silage was modelled simultaneously for each simulation, with inputs tailored to reflect each group's use of the rotational grazing system. The functional unit for the finishing system was defined as 1 kg of live weight gain (LWG), though emissions per day and per hectare were also calculated for each simulation.

4.2.3. Modelling a parent beef suckler system

A simulated beef suckler system was also modelled in AgRE Calc with the aim of providing a representative estimate of emissions intensity for suckler beef in the United Kingdom, providing context for the finishing system emissions. A literature survey was used to provide representative activity data, and to capture the variability in these parameters across the UK suckler beef industry, with the aim of accounting for this variability via Monte Carlo simulation.

Activity data sourced from QMS (2016) was utilised to characterise the herd parameters, whilst data from SAC (2016) was employed to estimate cattle live weights for three different systems. Table 4.2 presents the ranges and sources for the identified parameters. Growth rate and age at sale for production animals on all systems were set at 0.951 kg hd^{-1} day^{-1} and 167.1 days, to reflect the average weight and age of animals entering the finishing system defined in section 4.2.1. Live weight gains for replacement bulls and heifers were set according to an assumed 40 kg birth weight and 24 month maturity, with mature live weights (and hence daily live weight gains) differing by system (SAC, 2016). Diets for production and replacement animals were defined in the model according to sample data from Morgan and Vickers (2016), HCC Wales (2006) and SAC Consulting (K. Stewart, pers. comm.), whilst for finishing animals, data supplied by the rearing system on which they were raised was used to estimate a ration consisting of concentrate feed and straw at a ratio of 11:1 (fresh weight). For variable growth rates, daily ration quantities were varied to reflect changing energy requirements, calculated as defined in Dong et al. (2006). Appendix section A.3 provides the raw ration data for these systems. Animals were assumed to spend seven months at grass vs. five months housed for every system type, with manure stored in solid storage for the housed period; data from SAC (2016) indicates these are reasonable assumptions. Dietary DE% and CP% were calculated by AgRE Calc (see chapter three of this thesis for derivation of methodology) and hence reflected the individual dietary composition. Digestible energy obtained from grassland was calculated using a constrained run of the model developed in chapters five and six of this thesis. Allocation of emissions between cull and finishing animals was handled economically, as in PAS2050 (BSI, 2011), using market data from SAC (2016). The functional unit of the simulation was defined as 1 kg of live weight (LW) at the farm gate.

Table 4.2. Activity data for the modelled beef suckler systems. Data is divided into three system types as in QMS (2016); Low = lowland system, LFA = less favoured area system, DA = disadvantaged area/hill system. Variable parameters were characterised using a uniform distribution.

Parameter	Unit	System	Min	Max	Source
Bulls per cow	**n/a**	Low	0.036	0.040	QMS (2016)
		LFA	0.034	0.044	
		DA	0.034	0.043	
Calving percentage	**%**	Low	85.0	92.0	QMS (2016)
		LFA	87.0	92.5	
		DA	90.0	91.0	
Calf mortality	**%**	Low	2.2	2.4	QMS (2016)
		LFA	1.1	4.0	
		DA	1.1	2.2	
Cow repl. rate	**%**	Low	11.0	13.0	QMS (2016)
		LFA	10.0	15.1	
		DA	7.0	9.0	
Cow mortality	**%**	Low	1.6	1.8	QMS (2016)
		LFA	0.9	2.4	
		DA	0.5	3.5	
Other cattle mortality	**%**	Low	0.0	1.4	SAC (2016)
		LFA	0.0	1.4	
		DA	0.0	1.4	
Live weight gain (repl. suckler cows)	**kg hd^{-1} day^{-1}**	Low	0.76		SAC (2016)
		LFA	0.83		
		DA	0.77		
Live weight gain (repl. bulls)	**kg hd^{-1} day^{-1}**	Low	1.10		SAC (2016)
		LFA	1.06		
		DA	0.97		
Milk production	**litres hd^{-1} year^{-1}**	Low/LFA	2,200		SAC (2016)
		DA	2,000		
Suckler cow adult live weight	**Kg**	Low	670		SAC (2016)
		LFA	650		
		DA	600		
Bull adult live weight	**Kg**	Low	1250		SAC (2016)
		LFA	1100		
		DA	1000		

Monte Carlo simulation was performed with 10,000 repeats to capture variability in the input parameters defined in table 4.2. Additionally, diets were also varied stochastically to capture the full extent of variability in the sample. Uncertainties in calculations of ration composition and grazed forage requirements (calculated following Dong et al., 2006), effectively representing real-world system variation, and were also modelled stochastically in the simulation. Epistemic uncertainties inherent in the emissions modelling process (explored in section 3.4 and chapter seven of this thesis) were not modelled stochastically here; this a) maintained focus on the variability and uncertainty in the herd parameters and b) maintained consistency of scope with the data available for the finishing systems. A mean and standard deviation for the emissions intensity across the three systems was then calculated, to provide an estimate for United Kingdom suckler beef production.

4.2.4. Modelling a parent dairy system

To provide a comparison for the simulated beef suckler system, a hypothetical dairy system was modelled as the progenitor for the finishing cattle. The overarching aim for the approach was similar to the modelled suckler system in that Monte Carlo simulation was used to provide an estimate of the variability present in the industry; however, in deference to difference in the structure of the UK dairy industry, the specific approach followed was slightly different.

A mean milk yield estimate (in litres hd^{-1} $year^{-1}$) for a typical contemporary Scottish dairy system was derived from breed-specific performance statistics from CDI (2015), weighted by breed number data from the Economic Report on Scottish Agriculture (SGDEF/RESAS, 2016). The same approach was used to estimate milk butterfat and protein percentage. Data from SAC (2016) was used to estimate a range of variability around milk yield (table 4.3), and based on the same source, linear relationships were established between milk yield and several additional performance parameters; dairy cow mature weight, herd life, calving interval, and proportion of concentrates in the ration (equation coefficients are defined in appendix section A.4). To account for covariance in the simulation, ordinary least squares (OLS) regression equations (Kenney & Keeping, 1962) were used to link these variables to the Monte Carlo parameter for milk yield.[12] Ranges for these parameters are presented in table 4.3.

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[12] N. B. A copula would typically be used for this purpose in MCS, but due to data constraints a copula fit was not possible

Table 4.3. Data ranges and sources used to characterise dairy beef production. Linked parameters marked with a * were linked via OLS regression equation to the Monte Carlo variable for milk yield, using regression equations developed from Farm Management Handbook data (SAC, 2016) (see appendix section A.4). Available data suggested little or no variability around milk protein and butterfat percentage and these were assumed constant.

		Min	Mean/ best estimate	Max	Distribution type	Source
Bulls per cow	**n/a**	0.036		0.040	Uniform	SAC (2016)
Calving percentage	**%**	86.9		98.6	Linked*	SAC (2016)
Cow repl. rate	**%**	20.0		33.3	Linked*	SAC (2016)
Calf mortality	**%**	3.0		4.0	Uniform	SAC (2016)
Live weight gain (repl. dairy cows)	**kg hd^{-1} day^{-1}**	0.630		0.836	Linked*	SAC (2016)
Live weight gain(repl. bulls)	**kg hd^{-1} day^{-1}**	0.904		1.041	Uniform	SAC (2016)
Milk production	**litres hd^{-1} day^{-1}**	5,000	8,021	10,000	Beta PERT	CDI (2015) ERSA (2015) SAC (2016)
Milk butterfat	**%**		4.05		n/a	CDI (2015) ERSA (2015)
Milk protein	**%**		3.28		n/a	CDI (2015) ERSA (2015)
Ration concentrate fraction	**%**	9.68%		29.18%	Linked*	MAFF (1990) SAC (2016)

Rations were defined as in the 2015 United Kingdom Greenhouse Gas Inventory Report (originally from MAFF, 1990). Concentrate fraction was varied according to relationship with milk yield, based on data from SAC (2016); in addition to fed roughage (e.g. silage), grazed grass is included in this ration and hence time at grass also reflected milk yield (higher milk yield = higher concentrate % = less grazed grass in ration). Allocation between milk, cull cows and dairy beef was performed economically, according to PAS2050 (BSI, 2011) using 2015 market data for the value of dairy beef, dairy culls and milk (sourced from SAC, 2016).

Monte Carlo simulation was performed with 10,000 repeats to capture variability in parameters defined in table 4.3. The scope and boundaries of the uncertainty calculation were the same as described for the beef system (section 4.2.3). The simulation differed, however, in that only one system type was modelled; this is representative of differences between the suckler beef and dairy industries (SAC, 2016), and meant that intra-systemic variability accounted for all uncertainty in this modelled dairy system. A mean and standard deviation for the emissions intensity of the modelled system was then calculated, providing an estimate for UK dairy beef production.

4.2.5. Statistical analyses and software

A version of AgRE Calc based in Microsoft Excel was used to provide estimates of emissions intensity for individual animals within the finishing system. Microsoft Visual Basic for Applications (VBA) was used to automate the footprinting process. Monte Carlo simulation for the calculation of concentrate production emissions, and of emissions from the suckler and dairy parent systems, was carried out using Vose ModelRisk.

For the statistical analysis of the results data, parametric assumptions were confirmed using the Anderson-Darling test for normality and Levene’s test for homogeneity of variance. One-way ANOVA and Tukey’s HSD post-hoc test were used to assess the statistical differences between emissions intensity estimates for different groups, for a) the finishing systems alone, b) the suckler beef-linked finishing systems, and c) the dairy-linked systems. OLS regression analyses (Kenney & Keeping, 1962) were used to identify the effectiveness of average live weight (ALW) and live weight gain (LWG) as predictors for emissions intensity of the finishing period. Significance level for all analyses was set at $p = 0.05$. All statistical analyses were carried out in the statistical computing language R (R Core Team, 2017).

4.3. Results

4.3.1. Finishing performance

All groups in the experiment completed the finishing period according to the approach defined in section 4.2.1. Whilst diets and growth patterns were projected (section 4.2.1), growth patterns were prioritised and diets were adjusted accordingly. Fig. 4.2 details the growth trajectories, through to final weight at slaughter, for the animals over the finishing period; table 4.4a gives the achieved daily LWGs. Concentrates were added, in varying amounts, to the housed diets of groups A-C to ensure that target LWGs were achieved (table 4.4b).

Table 4.4a. Achieved LWGs (in kg hd^{-1} day^{-1}) ± 1 *S. D.* for each of the groups across the finishing period. Note that final season duration varies between groups depending on slaughter date (see figs. 4.1, 4.2). Entries shown in bold are < 1 *S.D.* from their projected LWG for the season; entries in italics deviated by > 1 *S.D.* from this trajectory.

	First winter	First summer	Second winter	Second summer
A	**1.14 ± 0.11**	*0.78 ± 0.10*	*1.57 ± 0.4*	-
B	**0.88 ± 0.13**	**0.73 ± 0.13**	*1.25 ± 0.17*	-
C	**0.53 ± 0.08**	**1.10 ± 0.17**	*1.47 ± 0.14*	-
D	**0.53 ± 0.08**	*0.70 ± 0.14*	*0.82 ± 0.14*	*0.84 ± 0.19*
E	*1.33 ± 0.11*	**1.17 ± 0.14**	-	-
F	*1.36 ± 0.13*	**1.01 ± 0.23**	-	-

Table 4.4b. Final concentrate inclusion in the finishing rations (in kg FW hd^{-1} day^{-1}). For groups E and F, the first winter and summer represented a continuous housed period. Note that groups A, B and C had provision for *ad lib* concentrate inclusion in the ration to maintain target growth paths.

	First winter	First summer	Second winter	Second summer
A	3.24	0	6.37	-
B	1.57	0	0	-
C	0	0	3.27	-
D	0	0	0	0
E	10.27		-	-
F	10.39		-	-

Group A were targeted to grow at 1.1 kg hd^{-1} day^{-1} throughout the finish. This rate was met (to within 1 *S.D.*) the first winter, though on turning out to grass, the growth rate dropped markedly. This was partially corrected in the second winter, though as a result, the overall growth rate was slower than the concentrate-based groups E and F; these two groups had the same anticipated trajectory, though exceeded it for the majority of their finish (Fig. 4.2). Groups B and C followed their anticipated growth trajectories for the first two seasons, though exceeded them for the second summer. Group D followed the anticipated trajectory for the first season, though exceeded it in the first summer. Following this, the growth rate increased, though fell below the target amount (1.1 kg hd^{-1} day^{-1} for the final two seasons was anticipated). Overall, the fastest growth rates were shown by animals in groups E and F, followed respectively by group A, groups B and C, and group D (Fig. 4.2). Owing to differences in the duration of the finish, the heaviest slaughter weights were found in groups B, C and D, with the lightest animals in groups E and F and group A representing an intermediate.

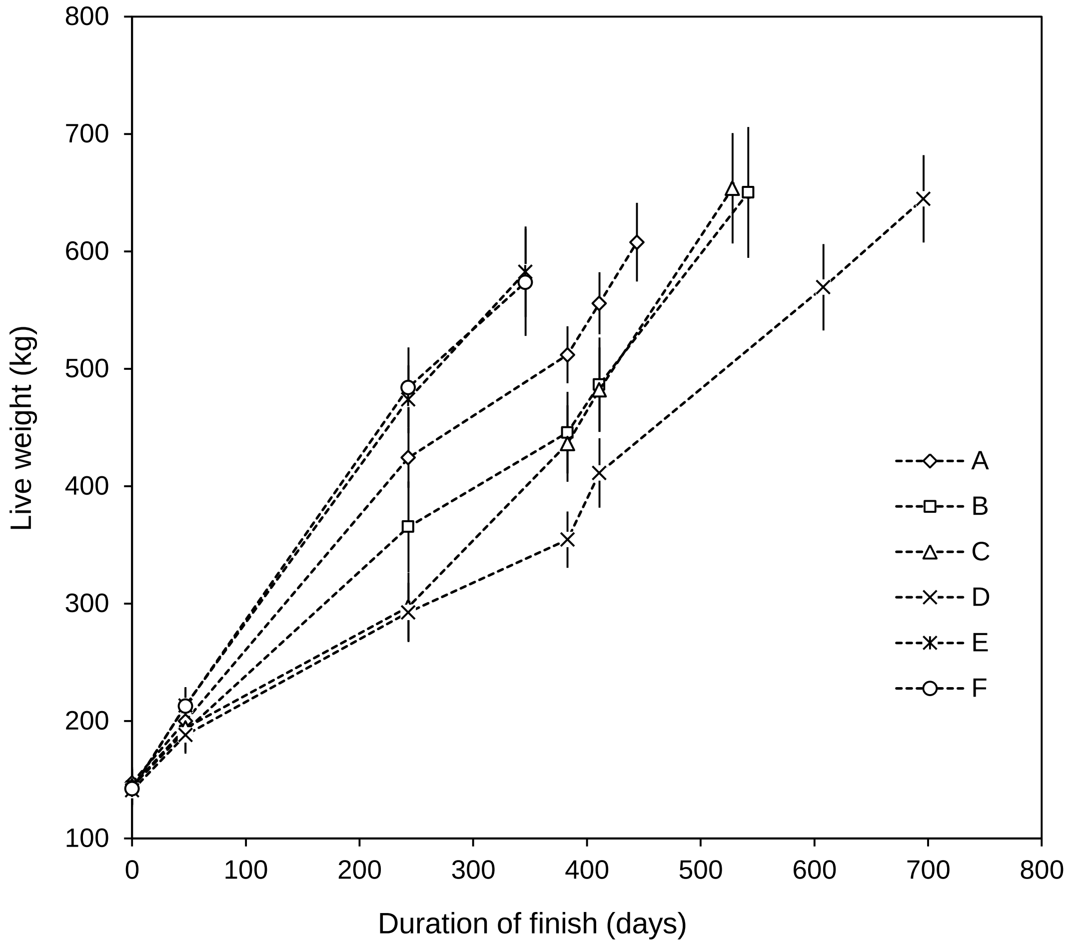

Fig. 4.2. Live weight gain performance of animals during the finishing period. Error bars show within-group standard deviations. The date of first weighing (x = 0 days) was August 15th.

4.3.2. Emissions intensity of finish

Of 132 animals beginning the experiment, ten were removed over the course of the finish for reasons of health or performance, leaving 122 animals at slaughter for which carbon footprints could be calculated (table 4.5). Animals from group D were found to have the highest average emissions intensity, with animals from groups A and C showing the lowest.

Table 4.5. Final sample sizes and overall emissions intensity (in kg CO_2-eq kg LWG^{-1}) results for the six finishing groups.

	N	Mean	Std. Dev.	Min	Max
A	21	9.31	0.39 (4.2%)	8.66	9.98
B	21	9.51	0.41 (4.3%)	8.87	10.61
C	21	9.32	0.45 (4.8%)	8.69	10.10
D	20	11.54	0.42 (3.6%)	10.64	12.08
E	21	9.47	0.55 (5.8%)	8.60	10.61
F	18	9.86	0.60 (6.1%)	8.99	11.19

The highest range of emissions was shown by the concentrate groups, with E and F showing a range of 21% and 22% of the mean respectively. Group D had the most consistent emissions intensity between individuals, with the range at 12% of the group mean.

Breaking down the emissions intensity estimate into source categories, it was found that group D showed the highest contribution from enteric methane, with groups E and F showing the lowest (Fig. 4.3). With two seasons on grass (albeit on less intensively managed swards than groups A-C), group D also had the greatest contribution from field N_2O (from application of fertiliser/manure and from grass residues) and fertiliser production. Emissions from groups E and F were dominated by the production of purchased feeds, the majority of which were concentrates. Manure management emissions were relatively constant between the groups, and differences scaled proportionately with the duration of the finishing period. Emissions from groups A, B and C were most heterogeneous, with contributions of comparable scale provided by manure N_2O, field N_2O, fertiliser production, and feed production.

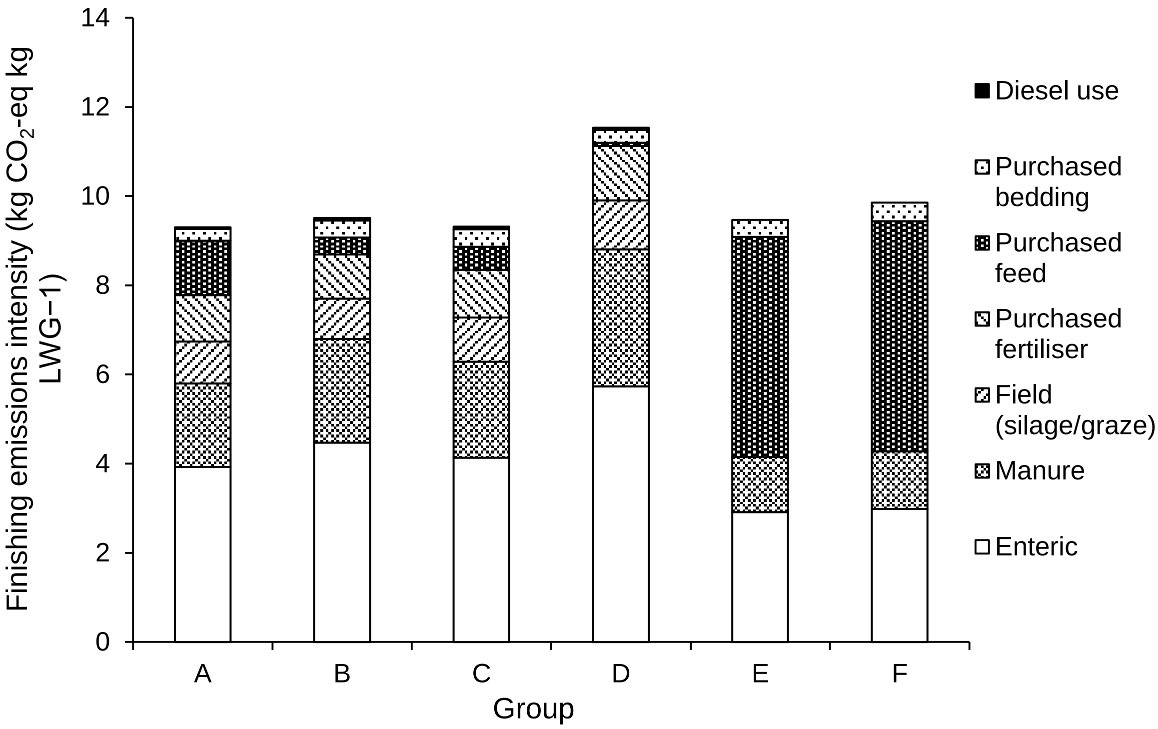

Fig. 4.3. Breakdown of finishing period emissions intensity into source categories. The 'Field (silage/graze)' emissions category relates only to N_2O emissions from managed grassland; embedded emissions from fertiliser production are shown separately.

As the longest duration finish, group D produced the highest total emissions (5,274 ± 293 kg CO_2-eq hd^{-1}), though average emissions per day were the lowest of any group (Fig. 4.4). The lowest overall emissions were produced by groups E (3,472 ± 166), F (3,551 ± 165) and A (3,582 ± 156) (Fig. 4.4). Groups E and F also produced the highest emissions per day.

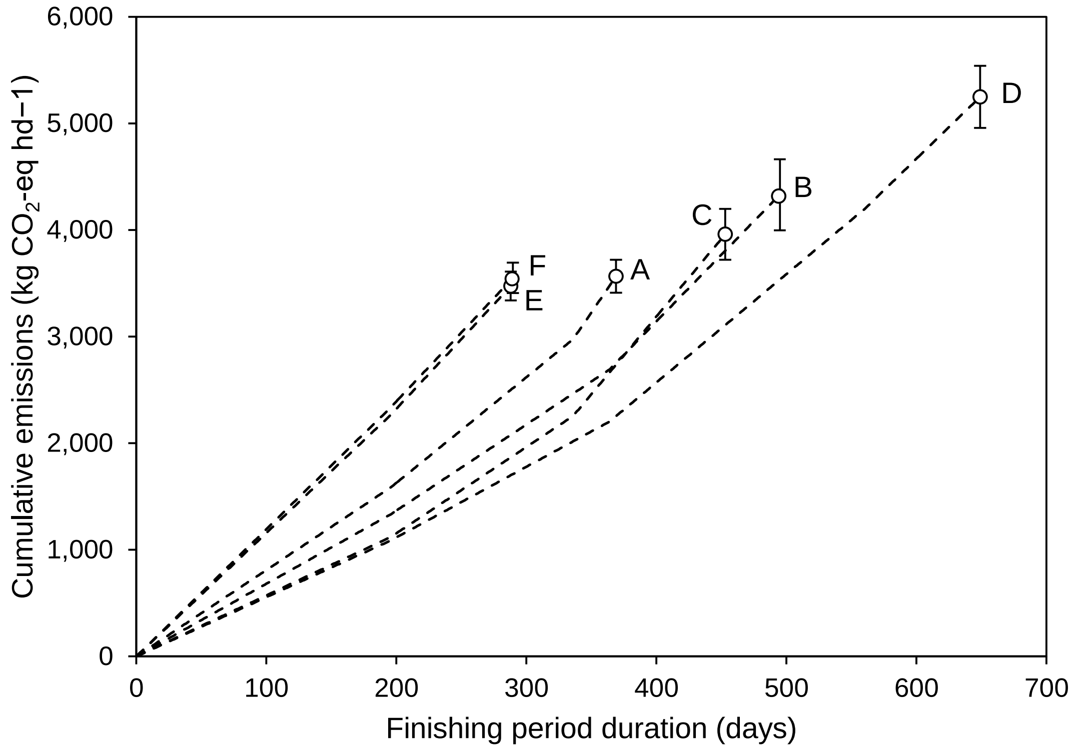

Fig. 4.4. Cumulative emissions (in CO_2-eq hd^{-1}) over the course of the finishing period. Error bars show ± 1 *S. D.*

Considerable within-group variation existed between seasons (table 4.6). For groups A and B, the housed period represented a less emissions intensive part of the finish; the reverse was true for group C and, to some extent, group D. As a general trend, emissions intensity increased as the finishing period progressed.

Table 4.6. Emissions intensities (in kg CO_2-eq kg LWG^{-1} ± 1 *S. D.*) by season for the six finishing groups. Entries in italics represent periods where animals were at grass; entries in bold were housed.

	First winter	First summer	Second winter	Second summer
A	**7.16 ± 0.43**	*12.79 ± 1.24*	**11.83 ± 1.59**	-
B	**7.9 ± 0.63**	*11.28 ± 1.75*	**10.14 ± 0.58**	-
C	**11.18 ± 1.39**	*7.44 ± 0.72*	**10.05 ± 0.45**	-
D	**10.68 ± 1.25**	*9.74 ± 1.67*	**12.74 ± 1.38**	*14.74 ± 3.51*
E	**8.74 ± 0.49**	**11.31 ± 0.96**	-	-
F	**8.82 ± 0.54**	**13.38 ± 3.15**	-	-

Utilising the values shown in table 4.6, regression analyses were employed to explore the effect of live weight gain (LWG) and average live weight (ALW) on the emissions intensity of production (Fig. 4.5). It was found that LWG did not show a significant effect on the emissions intensity (*DF* = 15, *F* = 0.45, R^2 = .029, *p* = .51), but that ALW was a significant predictor (DF = 15, F = 8.52, R^2 = .362, p < .01), with emissions intensity increasing for heavier animals.

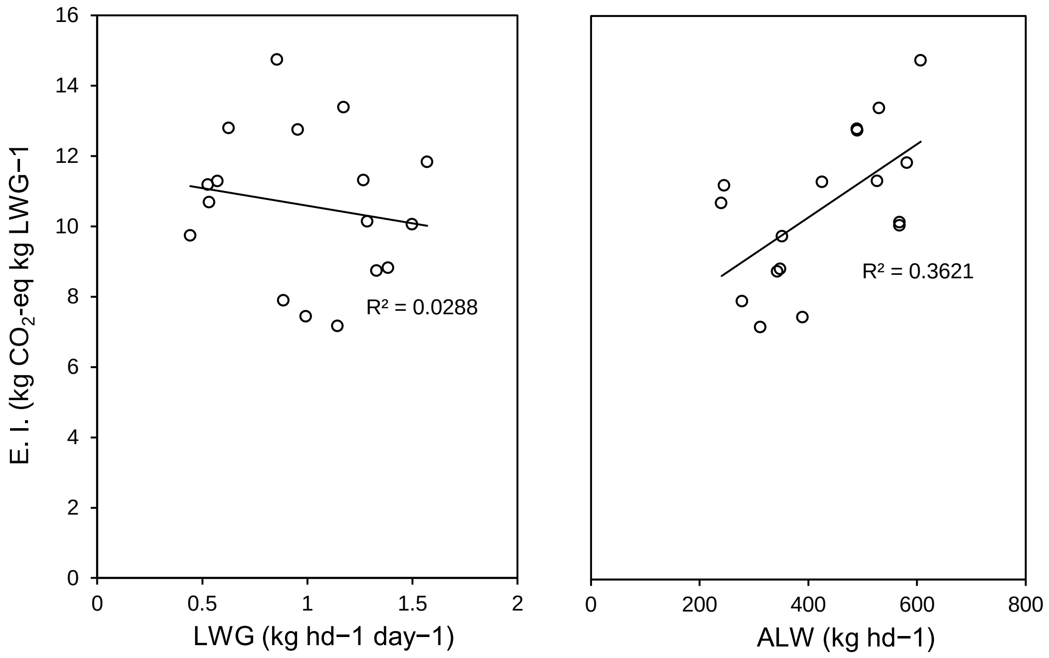

Fig. 4.5. Emissions intensity (EI) plotted against daily live weight gain (left) and average live weight (right) for each of the separately calculated carbon footprints (each comprising a different finishing group and time period).

4.3.3. Emissions from parent systems

Monte Carlo simulations of 10,000 runs were completed to provide an emissions estimate for the hypothesised beef and dairy parent systems. The dairy parent system produced finishing animals at an emissions intensity of 9.47 ± 0.45 kg CO_2-eq kg LW^{-1}. The finishing animal accounted for 12.4 ± 2.0% of the total system footprint, with the remainder allocated to milk (84.5 ± 1.2%) and cull animals (3.1 ± 0.9%). The suckler beef system produced finishing animals at an emissions intensity of 26.04 ± 4.57 kg CO_2-eq kg LW^{-1}. The finishing animal accounted for 80.5 ± 3.8% of the total system footprint, with the remainder (19.5 ± 3.8%) allocated to cull beef.

4.3.4. Lifetime emissions

Assigning the average suckler beef emissions intensity (26.04 kg CO_2-eq kg LW^{-1}) to the steer entering the finishing system, Fig. 4.6 plots the average emissions intensity over the course of the finish. Given the relatively high emissions intensity for the suckler system, all finishing systems acted to reduce the overall emissions intensity of the finished animal. In producing the lowest emissions per kg LWG, finishing groups A, E and F represented the steepest drop in emissions.

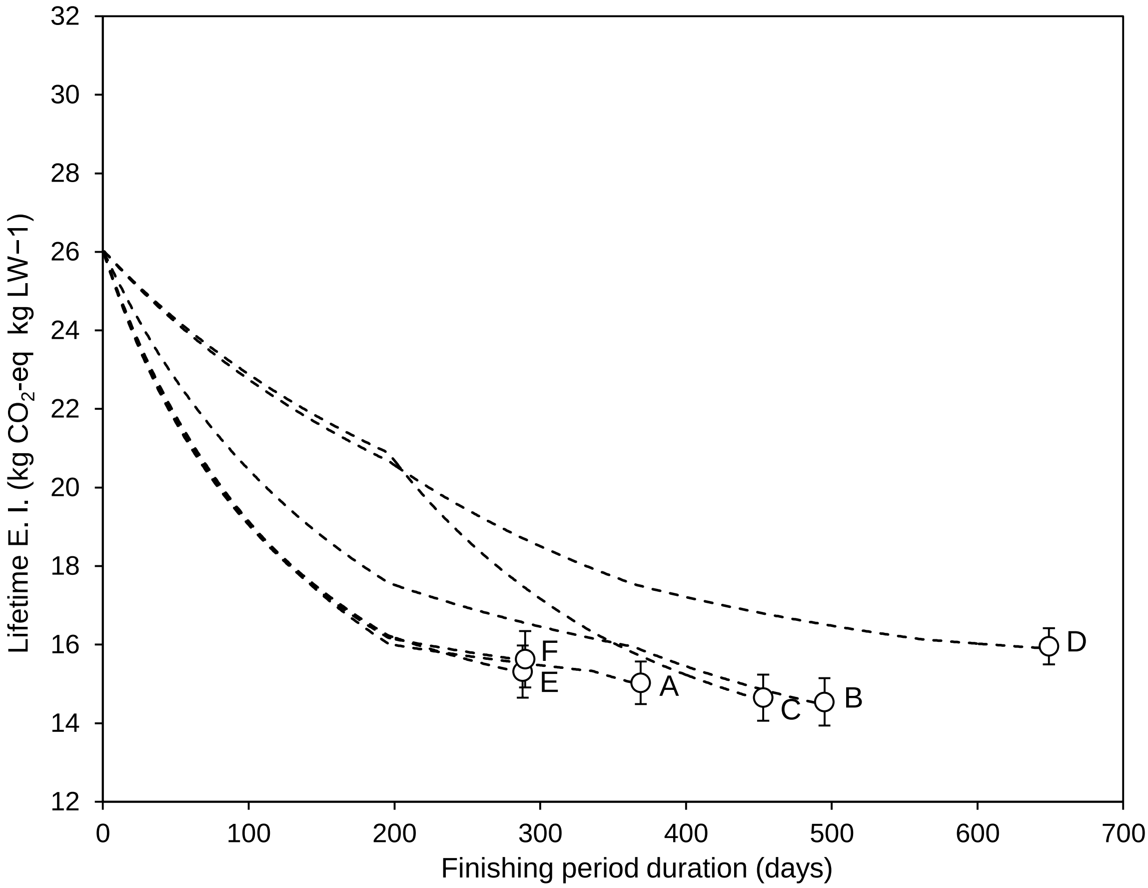

Fig. 4.6. Day-by-day emissions intensity shown over the duration the finishing period. Error bars show ± 1 *S. D.* Analysis assumes beef progeny; animals begin finish with an emissions intensity of 26.04 kg CO_2-eq kg LW^{-1}.

However, in finishing the animals at heavier weight, systems B and C acted to reduce emissions further than the shorter, lighter finishes (A, E and F). This was achieved despite having slightly higher emissions per kg LWG for the finish (table 4.7). It can also be seen that system D, though slightly higher than the overall mean, still represents a substantial drop in emissions intensity of the animals entering the finishing system.

For the dairy system, animals entering the finish were assigned the modelled mean emissions intensity from the production system of 9.47 kg CO_2-eq kg LW^{-1}. This is a similar value to the overall mean for the finishing groups (9.84 kg CO_2-eq kg LWG^{-1}), resulting in a variable direction of response when applied to the finishing systems (Fig. 4.7). The final mean EI was reduced by groups A and C, and increased by groups B, D and F. To the nearest 10 grams, the mean EI remained unchanged for group E.

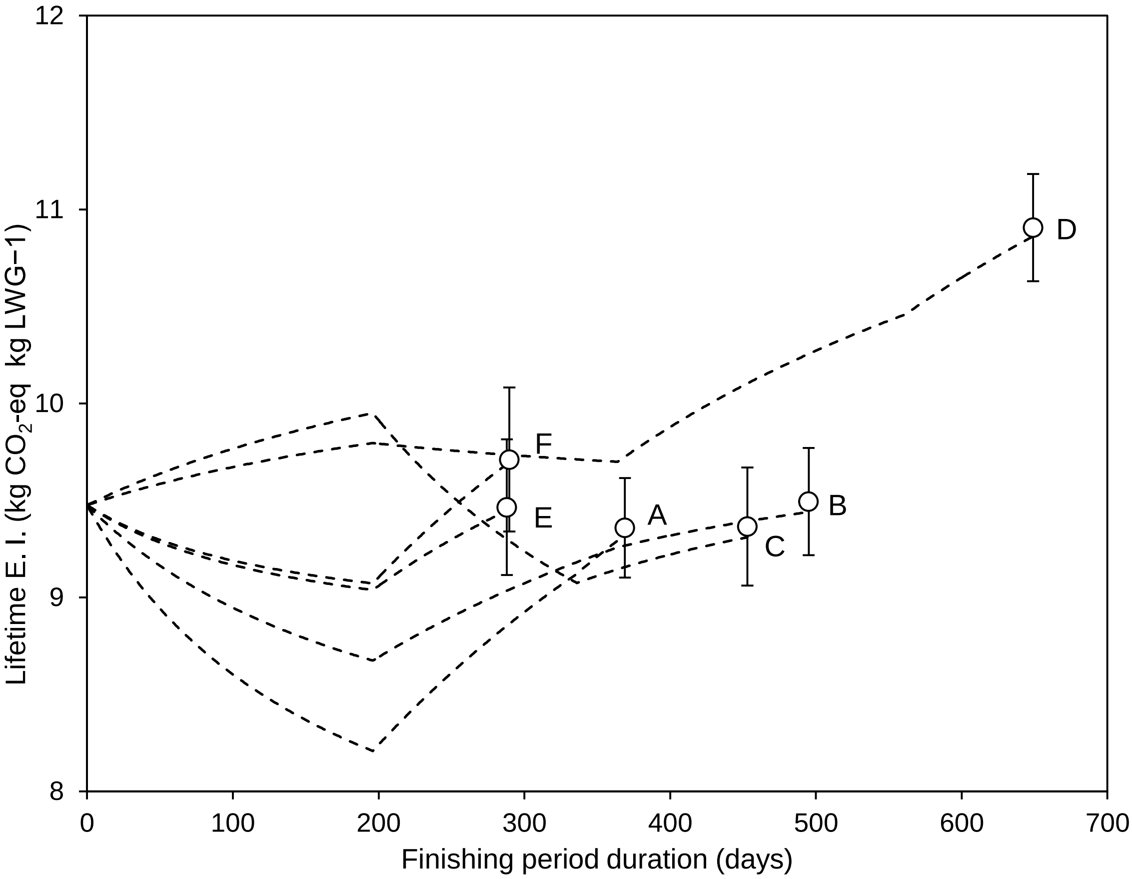

Fig. 4.7. Day-by-day emissions intensity shown over the duration the finishing period. Error bars show ± 1 *S. D.* Analysis assumes dairy progeny; animals begin finish with an emissions intensity of 9.47 kg CO_2-eq kg LW^{-1}.

Results from each system type were found to conform to parametric assumptions of normality and homogeneity of variance. ANOVA found statistical differences between the emissions intensity of groups for a) the finish alone ($F(5, 116) = 67.02$, $p < 0.0001$), b) the suckler beef-linked finish ($F(5, 116) = 17.28$, $p < 0.0001$) and c) the dairy-linked finish ($F(5, 116) = 76.38$, $p < 0.0001$). Tukey's HSD was carried out post-hoc to allow statistical grouping of the different finishing strategies (table 4.7).

Table 4.7. Mean emissions (in kg CO_2-eq kg $LW(G)^{-1}$) for the finishing period assuming a) no progenitor system, b) a beef progenitor and c) a dairy progenitor. Letters show statistical groupings (p < .05) based on ANOVA and Tukey's HSD post-hoc test.

	Finishing period only	Finishing beef progeny	Finishing dairy progeny
A	9.31^{a}	15.03^{ad}	9.36^{a}
B	9.51^{ab}	14.54^{a}	9.49^{ab}
C	9.32^{a}	14.65^{a}	9.37^{a}
D	11.54^{c}	15.96^{b}	10.91^{c}
E	9.47^{ab}	15.32^{cd}	9.47^{ab}
F	9.86^{b}	15.63^{bc}	9.71^{b}

For the finishing-only results, emissions intensities from groups A, B, C and E were not significantly different, though groups A and C (grass-based) were significantly lower than groups F (concentrate-based) and D (grass-based, long finish). Tukey's HSD showed that results from the finishing period alone and the dairy-linked finish were statistically similar, meaning inclusion of emissions from the dairy system did not alter the order or grouping of the results.

For the beef-linked finish, the revision to the expected order suggested by Fig. 4.6 was supported by the post-hoc test. Groups B and C (the longer, heavier finishes) were significantly lower than both concentrate finishes (E and F) and group D (previously significantly the most emissions intensive finish) was not significantly higher than group F.

4.4. Discussion

4.4.1. Finishing suckler beef

Overall, grass-based finishes of short to middling duration (groups A, B and C) were found to be the most efficient in isolation, with the concentrate-based finishes relatively similar, but more emissions intensive on average. It is worth noting that the two concentrate-based groups (E and F) were very similar in that the only difference was in levels of vitamin E supplement, and so the difference between groups E and F largely reflects different animal responses to this finishing type.[13] The slowest duration finish, group D, was the least efficient in isolation, with significantly greater emissions intensity than other finishes. Concentrate based groups (E and F) produced substantially more emissions per day than the grass-based finishes, though this was offset by a higher rate of daily LWG and an overall shorter finish.

The grouping of these results was changed when linked to the simulated suckler cow-calf system. Overall, the analysis of the suckler-linked finish showed clearly that the finishing systems act to reduce the lifetime emissions intensity of production; as such, it is useful to view the finishing system as an opportunity to capitalise on the emissions 'invested' in the suckler system; whilst longer durations may result in more emissions overall, they allow more opportunity for the finishing system to redeem this investment.

Longer, slower extensive finishes (e.g. group D) perform poorly in comparison to both intensive, housed finishes (E and F) and higher-input grass-based approaches (A, B and C) when viewed in isolation; this finding is well supported by a growing body of LCA literature (Casey and Holden, 2006; Pelletier et al., 2010; Cardoso et al., 2016). However, somewhat contrasting to the findings of these authors, in respect of the emissions load generated by the suckler production system, the longer extensive finish

[13] The rationale for the difference in diets E and F was to provide the basis for a (separate) assessment of the shelf life of the resulting meat, and both diets contained vitamin E in excess for the purposes of animal health. It is therefore deemed highly unlikely that the difference in emissions intensities between groups E and F is as a result of dietary differences.

was found to perform more effectively. This was caused by the higher final weight of the group D animals (*M* = 645 kg) in comparison to the concentrate-based approaches. Groups B and C, which also finished at heavier weights (*M* = 650 and 654 kg respectively) faired best when linked to the beef system, with emissions intensities both significantly lower than the housed finishes (table 4.7). These results suggest that daily live weight gain is of less importance than final weight in determining the overall emissions intensity of production for finishing suckler beef.

The efficacy of grass-based finishes highlighted by this study contrasts, to some extent, with the results of much of the LCA literature; Pelletier et al. (2010) found that the enteric CH_4 mitigation effect of higher quality concentrate-based diets afforded by housed finishing systems was sufficient to reduce net emissions in US beef systems. Casey and Holden (2006), Hyslop (2008) and Vergé et al. (2008) found similar effects in Irish, UK and Canadian systems respectively, and additionally reported that shorter finishes could act to reduce emissions. The results of this study find that, in the case of suckler beef, this may be a false economy; the heavy emissions load from the suckler system means that heavier (and longer) finishes may be more appropriate. Results from this study also challenge the view that feedlot finishing is the most efficient approach; the grass-based systems modelled here performed as effectively as, and in some cases better than, the housed finishes. It is worth noting that some of the merits of the grass-based systems reported in this study may be due to the emphasis on rotational (as opposed to continuous) grazing; it is likely that this practice contributed to a more efficient utilisation of grazing, and maximised the number of animals between which the emissions overheads associated with grazing land maintenance could be shared. Supporting this, DeRamus et al. (2003) show that best management practices in grazing systems can substantially reduce GHG emissions.

The slaughter date for each of the suckler beef finishing strategies represented the lowest point in the emissions intensity trajectory (Fig. 4.6). As such, all of these systems could be judged ‘successful’ in terms of reducing emissions from the suckler phase. However, as previously discussed, the finishing systems can be seen as a way of reducing the overall emissions intensity of production (given the high emissions load from the suckler system), and to this end it is useful to explore the extent to which this could continue. The final gradient of the EI curve (Fig. 4.6) can be taken as a basic indicator for the potential of each finishing system to continue to lower the overall emissions intensity of production; a more level curve indicates that the system is approaching its average EI and as such has lower remaining potential to reduce the overall intensity. Interestingly, groups B and C, which had the lowest final emissions overall, also had some of the steepest final gradients (−8.5 and –10.8 g CO_2-eq kg LW^{-1} hd^{-1} respectively), indicating that this system had the potential to further lower emissions intensity. Cattle from groups B and C were slaughtered at relatively heavy weight (*M* = 654 kg; heavier than groups A, E and F, and on par with group D), suggesting that whilst continuation of this approach may be possible, it would be important to consider the genetic growth potential of the animals, and the resulting decrease in performance this may incur.

4.4.2. Finishing dairy beef

For the dairy-linked finish, the emissions intensity over time was somewhat more variable, owing largely to the lower emissions intensity carried to the finish by the dairy-bred animals. Several of the finishing groups (A, B, E and F) dropped in emissions intensity over the first winter, and increased again over the following seasons (Fig. 4.7). Whilst group C represented the most efficient finish overall, groups A and B could have undercut this by a considerable margin if the animals had been slaughtered after the first winter. The average LWG hd^{-1} for groups A and B were significantly higher during the first winter than the following summer; this is largely responsible for the concurrent increase in emissions intensity. By contrast, group C grew slowly, with lower quality feed, for the first winter, and subsequently experienced high compensatory growth when put out to high quality pasture the following summer. The diets of groups E and F did not vary greatly between the first winter and summer (they remained housed throughout), but the emissions intensity of the finish increased considerably following the change. This may be due to the increased live weight of these animals, requiring larger amounts of concentrate feed to maintain high rates of daily LWG; emissions from the production of concentrates dominated this footprint (Fig. 4.3) and it is likely that increases would have a marked effect. Life cycle studies of intensified beef systems (e.g. Pelletier et al., 2010; Hünerberg et al., 2014) corroborate this finding. It is probable that the increase in emissions intensity of groups E and F was more gradual than the trajectories shown in Fig. 4.7 would indicate, though frequency of live weight and feed supply measurements preclude further exploration of this.

For group D, the emissions intensity of the dairy-linked finish did not vary greatly until the second winter, when an increase in daily live weight gain (from 0.5 to 1.1 kg hd^{-1} day^{-1}) was targeted, with the corresponding increase in feed supply resulting in an overall increase in emissions intensity from this point on. This was exacerbated by the fact that these animals grew considerably more slowly than the targeted 1.1 kg hd^{-1} day^{-1} for the final two seasons. These results suggest that slow growth, extensive finishes may to some extent be an acceptable approach for dairy bred animals, but while they do not unduly raise the carbon footprint, they forgo opportunities to reduce it. Additionally, increases in intensity of the finish at a late stage (where the animals are already heavier) may adversely affect the emissions intensity.

4.4.3. Predictors of emissions intensity

Regression analyses showed emissions intensity to be significantly affected by animal live weight (Fig. 4.5). This is explicable given the higher energy requirements of heavier animals (Dong et al., 2006); as a result, they require larger rations, and enteric methane and manure production increase. This causes a ‘double-hit’ in emissions, which increase as a result of both increased feed production and direct emissions from the animal. Additionally, heavier animals are closer to their genetic potential in terms of mature live weight; once closer to maturity, the growth curve begins to level (Kersey & Brinks, 1985), and as such the maintenance of a linear growth path may require greater levels of input, with correspondingly higher emissions. Animals in groups C and D were targeted to increase the LWG day^{-1} as the finish progressed (table 4.1) and animals in groups A-D all grew fastest at later stages (table 4.4a). It may be, therefore, that relationship between kg CO_2-eq kg LWG^{-1} and ALW demonstrates the additional emissions cost of increasing the growth rate of already heavy animals. As such, it may be possible to avoid this to some extent by maintaining a more even growth path throughout the finish.

By contrast, live weight gain alone was not found to have a significant linear effect on emissions intensity. Faster-growing animals have a higher daily energy requirement (Dong et al., 2006) and hence have higher feed intake and produce more enteric emissions and manure. However, it appears that the additional emissions this incurs were to some extent offset in the current study by the increase in live weight gain, rendering a negligible net difference in the emissions intensity (in kg CO_2-eq kg LWG^{-1}).

Some further insight may be gained by examining the groups' performances over the first winter; here, the groups are most comparable in that the animals were balanced for live weight between groups and all were housed. For the first winter, it appears that there may be an optimum daily LWG of around 1.1 kg hd^{-1} (Fig. 4.7). Group A had the lowest emissions intensity for this period at around this rate, whilst faster growing groups (E and F) and slower growing groups (B, C and D) were less efficient. This specific optimum value is of course relatively specific to the animals in this experiment, but the principle may apply more broadly. It is also worth noting that groups whose growth was constrained for the first winter (C and D) performed much more efficiently when turned out to grass than those groups which had grown faster over this period (A and B).

Animals in northern hemisphere production systems are typically housed for the winter period (e.g. HCC Wales, 2006; Morgan and Vickers, 2016). This study finds that emissions intensity between housed and grazing periods of a finishing system vary, though not always predictably. Depending to an extent on grass quality, results from group C suggest there may be some advantage to not pushing animals to grow quickly during the housed period; the compensatory growth shown at turnout by this group was advantageous in terms of both overall performance and emissions intensity.

4.4.4. Trade-offs and considerations for grass vs. concentrate finishes

This study found that concentrate-based finishes, such as groups E and F, offset a great deal of enteric emissions for emissions associated with feed production. This has been recognised by a number of previous studies (Casey and Holden, 2006; Beauchemin et al., 2008; Hünerberg et al., 2014), and though the exact balance of this trade-off is determined by a number of variable factors (Hünerberg et al., 2014), the amounts (measured in CO_2-eq) are typically approximately equivalent. As such there are a number of implications which should be considered. Firstly, moving from a grass-based to concentrate-based finish, a large proportion of the GHG emissions are effectively switched from CH_4 to N_2O. Comparisons between these gases are not clear cut; represented by the 100-year Global Warming Potential (GWP_{100}), the amounts (in kg CO_2-eq) are approximately equivalent. However, it is important to understand that the GWP_{100} is a physical metric derived from the lifetimes and radiative forcing values of

GHGs (IPCC, 2013), and the 100-year timescale is relatively arbitrary, though widely used. Uncertainties for the GWP_{100} are ±40% and ±30% for CH_4 and N_2O respectively, and absolute GWP estimates vary depending on the assumptions and timescale employed. Additionally, modelling uncertainties for the emission of N_2O are considerably higher than for enteric CH_4 (Dudley et al., 2014; see also chapter seven of this thesis), which may affect confidence in results. Another point to consider is that CH_4 is relatively short-lived in the atmosphere, but exhibits high radiative forcing throughout its lifespan (IPCC, 2013); correspondingly, its 20-year GWP is much higher in relation to the GWP_{20} for N_2O, which may be worth considering if short term GWP is of interest.

There are also uncertainties related to production practices for concentrate feeds. Concentrate feed typically contains multiple ingredients, for which production emissions estimates must be made and combined as described in section 4.2.2. These ingredients may be imported from abroad, where production practices are less certain, and transport and processing emissions must be included. Accounting for all of these stages and processes in a modelling framework requires reliance on assumptions (e.g. Vellinga et al., 2013), which may serve to increase uncertainty. Additionally, there may be additional emissions associated with land use change (LUC), particularly in developing nations with expanding agricultural areas, required to produce these ingredients; Flysjö et al. (2012) found that LUC impacts could affect the carbon footprint of beef production from +50% to −40%. Given that concentrate ingredients are typically arable crops, this LUC is likely to be either grass-arable or forest-arable, both of which represent an increase in emissions (IPCC, 2006). Even where ingredients are produced at home, production practices vary between regions and individuals which may impact emissions. Effectively, concentrate-based systems rely heavily on inputs from external sources, where emissions are more difficult to account for, and variability is outside the control of the production system manager.

It has also been observed that grassland-based livestock systems provide services which are not provided by an equivalent housed system (Beauchemin et al., 2010). One of the most important in the context of GHG accounting is the potential for soil carbon storage. De Oliveira Silva et al. (2016) showed that the potential for soil carbon sequestration as a result of increased investment in renovation of poor quality pastures by the Brazilian beef industry could act to offset production emissions. In the UK, well maintained pastures are likely to maintain considerably higher carbon stocks than the equivalent arable land required to support a housed beef production system (Ostle et al., 2009).

The grassland considered in this study is relatively high quality; the ability of finishing systems B and C to outperform the housed systems rests to some extent on this fact. The favourability of such areas mean that frequently, they are available for conversion to arable cropping, with corresponding losses of carbon stocks from the soil (Ostle et al., 2009). As such, it should be considered that livestock systems such as this may play a role in preventing emissions associated with grassland-arable LUC, and ensure continuous investment in the utilised grassland, which may act to promote the accumulation of soil carbon (Rutledge et al., 2017a; Rutledge et al., 2017b). As the majority of finishing systems in the United Kingdom are likely to be performance-focused, it is arguably likely that grass-based finishing systems utilise similarly high-quality grazing land and invest in its renovation. Uptake of this approach to beef finishing may consequently be limited to areas where high quality grazing land is available.

Beef production also plays an important role in utilising poorer-quality grasslands (EBLEX, 2009), though in the United Kingdom it is likely to be cow-calf suckler systems which occupy this land type (QMS, 2016) (this factor was accounted for in the modelled suckler beef system in this study). The role of extensive, low input grazing systems in soil carbon sequestration is less clear; overgrazing without adequate management can result in soil carbon losses (Lal, 2004), though Follett and Reed (2010) found that there may be some positive impacts from extensive grazing on US rangelands.

Where extensive grazing is the basis of production, there is an argument to suggest that beef systems represent a method of producing human-edible protein from land which would otherwise be unproductive in this respect (e.g. EBLEX, 2009); however, this argument is to some extent negated where higher quality or arable land plays a significant role in production. An important consideration is therefore the role of beef as a premium food product; this is shown by trends in developing nations, where consumption tracks increases in per capita GDP (Sans & Combris, 2015). This is difficult to quantify in LCA, though is to some extent reflected in the use of an economic approach for allocation of emissions between cull and sale beef (BSI, 2011). As a premium product, production practices are of importance to the consumer (Mennecke et al., 2007), and grass-fed beef may be seen as healthier or higher quality (Nuernberg et al., 2005). Beef from dairy-bred animals may also be perceived as lower quality in comparison to dedicated beef production systems. This is likely to be considered in the context of finishing approaches; it may make more sense commercially to focus grass-finishing on ‘premium’ suckler-produced beef, with concentrate-based finishes for dairy animals. The results of this study back this observation, with results indicating that grass-based finishes represent the greatest efficiency for suckler beef, with shorter, faster finishes (potentially housed) representing a good approach for dairy-bred animals.

A final consideration worth noting is that of finishing duration. This assessment makes the implicit assumption that emissions following the end of the finishing period are zero, i.e. that differences in system duration are of no consequence other than their immediate effect on direct system emissions. Particularly given the seasonality of the grass-based finishes and parent systems, beef finishing is inextricably linked to seasonal changes, and this may well play a role in a real-world choice of finishing duration. The assessment could be broadened to consider the wider consequential impacts of differently timed finishes on emissions from linked production systems; this could serve to ensure no false economies of mitigation are suggested in the context of broader agricultural systems.

4.4.5. Emissions from parent systems

Emissions from dairy beef were much lower than emissions from suckler beef. Production of milk offsets a large proportion of the emissions from dairy beef, rendering the emissions intensity of the dairy-produced animals (at the gate of the production system) around one third that of those produced in the suckler system. This result backs the findings of a growing body of literature which has considered dairy-produced beef (Crosson et al., 2011). A point worth noting in making this comparison is that dairy production in the United Kingdom is typically confined to lowland, high-producing pastures (SAC, 2016), whereas suckler beef production spans a much broader spectrum of land type and quality. This is reflected in the modelled scenarios in this study, and has a number of implications both for the estimated emissions intensity, and for the context in which it should be interpreted.

As a result of this, the beef system also showed much greater variability in the estimate (*S.D.* = 5.7 kg CO_2-eq) compared to the dairy system (*S.D.* = 0.3 kg CO_2-eq), proportionally to the magnitude of the emissions intensity. This was a direct result of the variability in the national-level activity data, which was much higher for beef production systems. By contrast, dairy production was effectively represented by only one system, albeit with varying levels of intensity within this. By contrast, the proportion of the dairy system emissions shared by the dairy beef animals was much more variable (*S.D.* = 1.9% for dairy vs. 0.3% for beef), owing largely to the modelled variability in milk production by the dairy system; lower-producing systems had proportionally less milk with which to offset the emissions from the finishing animal.

To maintain simplicity, this study employed the mean estimates for both parent systems ($M_{suckler}$ = 26.04, M_{dairy} = 9.47 kg CO_2-eq kg LW^{-1}) in order to assess the efficacy of the finishing systems in this context. However, it is worth noting that variability in the parent systems could affect the ideal choice of finishing system for the progeny; this is especially pertinent in the beef system, where variation was highest. A lower emissions estimate for the parent suckler system (95% CI_{lower} = 17.08) would have little impact on conclusions, given that finishing groups B and C (high quality grass finish) were identified as most efficient for both suckler beef and dairy bred animals. However, a higher estimate (95% CI_{upper} = 35.00) would further favour heavier finishes which capitalise more on the 'invested' parent emissions. Brief assessment suggests that a parent system emissions load of 35.00 kg CO_2-eq kg LW^{-1} would render finish types E and F less efficient than the grass-based finishes (A-D). This is a pertinent consideration for global beef production; in the UK, an estimate this high this could be deemed the exception, though for extensive rangeland-based production in developing nations (e.g. Modernel et al., 2013; Cardoso et al., 2016), emissions intensity values in this range are more common.

Finally, it is worth noting that in both modelled scenarios, the finishing animals were reared away from their dams for the majority of the rearing period; this was reflective of the real-world treatment of these animals. In dairy, it is common practice to raise calves away from cows (to allow the cows to produce milk for human consumption); however, in suckler beef systems, calves may be suckled for a proportionally longer weaning period. The feed for the suckler beef calf represented 2.16 kg CO_2-eq kg LW^{-1} (8% of the total emissions intensity) for animals leaving the modelled system; this value could be somewhat lower if animals were suckled for a longer proportion of the weaning period. Nonetheless, it forms a small part of the overall footprint for this system, and the emissions estimate for suckler beef production remains considerably higher than the dairy estimate.

4.5. Conclusions

For suckler beef systems, longer, heavier finishes were found to be more efficient given the heavy initial emissions load. By contrast, shorter, concentrate-based finishes did not represent an effective return on the emissions invested in the suckler system. Grass-based finishes, given quality pasture and best practice management, may be as or more efficient than housed, concentrate based approaches. This is particularly true where a heavy emissions load is carried by animals entering the system, and contrasts with a growing body of literature which advocates shorter, housed finishes. For dairy based systems, the emissions load carried by the animals entering the finishing system is much lighter, and on par with the emissions intensity of the finish. Shorter finishes are therefore more acceptable, though grass-based finishes may still be appropriate; results also suggest that extremely high daily LWG approaches may not represent optimum efficiency. The emissions intensity of a period also tracked relatively closely with average live weight; though DLWG was not a significant linear predictor for emissions intensity, many groups were pushed to grow fastest during their final (heaviest) period, and results suggest that this may be inefficient compared with faster growth earlier in the finishing period. Finally, performance was most variable for the fastest-growing, concentrate-based systems; improvement of animal genetics may therefore be one approach towards maintaining the efficiency of these.

Emissions profiles are very different for grass-based and concentrate-based finishing systems, with enteric CH_4 forming the majority of grass-based system emissions, and feed production emissions (mostly N_2O) dominating housed system footprints. This conclusion is consistent with results from the majority of research, though differs from some studies (Pelletier et al., 2010; Hyslop, 2008) in that here, feed production emissions outweigh enteric CH_4 for the majority of comparisons. This study also highlights the role that well-managed grass-based systems may play in the accrual of soil carbon reserves, which is unlikely to be matched by equivalent intensive production.

Results from this assessment serve to highlight the role of the finishing system in reducing the overall footprint of production. Previous studies have drawn attention to the emissions load from the cow-calf system as a focus for mitigation efforts (e.g. Beauchemin et al., 2011); whilst this study supports this to an extent, it also makes clear the role of the finishing system in ensuring overarching production efficiency. As a result, where efficiency improvements are sought in finishing systems it is important to quantify at a national level both the supply, and emissions intensity, of beef from suckler and dairy systems.

This study also demonstrates the usefulness of detailed, low-granularity datasets in generating statistically comparable LCA results. It also provides an indication of the uncertainty resulting from differences in animal performance likely to be present at the level of a single sample; this is not possible where estimates are generated on the basis of assumed performance. Data of this quality is difficult to source, but Monte Carlo simulation can be a useful approach to overcome this issue (e.g. Dudley et al., 2014; see also chapter seven of this thesis), and the variability in results identified herein may be of use to modellers relying on assumptions of performance.

Overall, this study adds to the body of literature on environmentally sound beef production, and provides an important and statistically supportable comparison of finishing strategies. Published LCA literature has tended towards the recommendation of housed, feedlot-style systems for environmentally efficient finishing; these results, to some extent, challenge that conclusion. Results also highlight the fundamental differences between the footprints, and the implications of these in a broader environmental context. Finally, this study highlights the requirement for consideration of the emissions from the production system when defining optimum finishing strategies, and finds that a move towards more efficient production systems will enable shorter finishes, with lower lifetime emissions.

Chapter Five

Modelling nutritional characteristics of grazing land for United Kingdom ruminant production systems

Part I: Definition and development of modelling approach

5.1. Introduction: required parameters and challenges

5.1.1. The role of grazing nutrition in beef production systems

Section 1.4.3 considered the role of grazing in beef production systems globally, and identified the characterisation of extensive production systems as a necessary challenge for mitigation of emissions globally. In addition, the analyses conducted in chapter four of this thesis identified grazed pasture as an important source of nutrition for animals in the sample system, and found that variations in the quality of pasture had an important effect on the emissions intensity of meat produced from the finished animals. Finally, characterisation of the pasture modelled in chapter four was made possible by the availability of laboratory-conducted measurements of nutritional quality; such data is rarely available in farm-level datasets. A stated goal of this thesis is to improve the ability of the AgRE Calc model to account for ration quality in estimation of emissions (section 1.4.3), and to maintain a low data input burden. In respect of the nutritional quality of grazing, these aims were not mutually compatible with the AgRE Calc model in its original state of development. These factors made clear the rationale for exploring approaches to account for this variable through use of existing input data.

The value of grass as a ruminant livestock feed is directly linked to its digestible energy (DE) content (Frame, 1992); the digestible energy of a feed is the gross energy (GE) content minus energy lost in the faeces (ILCA, 1990). Enteric CH_4 emissions are a by-product of the breakdown of carbohydrates by methanogenic bacteria (Dong et al., 2006), and so the digestibility of the feed also has a direct effect on the enteric emissions. Cattle rations with a higher percentage of GE as DE (a higher DE%) are digested more efficiently, and hence result in lower levels of enteric methane production and improved animal nutrition.

Manipulation of dietary digestibility has been well recognised as a potential mitigation approach for enteric emissions (e.g. Doreau et al., 2011; Mathot et al., 2012; Hünerberg et al., 2014). However, such approaches have typically focused on ‘fed’ rations (feeds supplied to the animal during housing or as supplementary feed at pasture). Producing more digestible feeds typically results in a trade-off of emissions; reduced methane production by cattle is counteracted by a more intensive production process, where greater emissions of N_2O and CO_2 result from higher use of fuels, energy and agrochemicals in the production process (Hünerberg et al., 2014).

5.1.2. Characterising grazed forage in the IPCC Tier 2 calculation of enteric methane

The IPCC provides a Tier 2 level approach for the calculation of emissions of enteric CH_4, manure CH_4 and manure N_2O from beef cattle (Dong et al., 2006). This approach has been utilised in numerous life cycle assessment (LCA) studies (e.g. Beauchemin et al., 2011; Cardoso et al., 2016), national-level inventories (Karimi-Zindashty et al., 2012; Milne et al., 2014) and farm-level models (Sykes et al., 2017). In order that this approach yields representative estimates, the digestible energy in the diet (DE%), crude protein in the diet (CP%) and dry matter content of feed (DM) must be accurately estimated. Whilst simpler approaches are available, it has been shown that a Tier 2 level approach to modelling livestock emissions is important in ensuring accuracy and flexibility of estimates (Caro et al., 2016; Sykes et al., 2017).

These parameters (particularly DE%) have the potential to significantly impact enteric and manure emissions (Dong et al., 2006). These are two of the largest emissions sources on most beef production systems globally (e.g Subak, 1999; Beauchemin et al., 2011; Cardoso et al., 2016). The enteric methane response to dietary digestibility is also non-linear, meaning in some cases small errors in calculation or estimation of DE can result in disproportionately larger errors in modelled methane production. Because of these factors, any errors in the estimation of these parameters will translate directly to a potentially substantial error in the final modelled value for most livestock systems.

Farm-level models to date, where a Tier 2 approach is followed (e.g. Hillier et al., 2011), tend not to explicitly consider factors such as DE% and CP% in the methodology, and instead rely on broader estimates for these parameters (relating to both grassland and fed rations). This is also typically true of national inventory calculations for which the IPCC (2006) calculations were originally designed; for example, the UK Greenhouse Gas Inventory Report (Brown et al., 2016) defines a standard DE% of 65% for all beef cattle. For LCA studies utilising a Tier 2 approach (e.g. Cardoso et al., 2016), where estimates of ration digestibility or crude protein are published, these also tend to be point estimates. Frequently, these values are not made explicit by LCA authors, which greatly limits the repeatability of the assessments.

There are a number of disadvantages to this approach. Firstly, it is difficult to accurately estimate DE% or CP% without expert knowledge of the system in question; this limits the ability of practitioners to model systems for which they do not have access to expert opinion. Secondly, there is limited scope for these estimates to vary in response to changes in animal ration, meaning emissions trade-offs relating to dietary manipulation of the type demonstrated by Hünerberg et al. (2014) are difficult to accurately assess. Thirdly, reliance on estimates for DE% typically means an annual average value is assumed, limiting the scope for dissection of the annual footprint into seasonal or sub-seasonal estimates, which can be important in identifying emissions hotspots (see, for example, chapter 4 of this thesis). Finally, given the sensitivity of the overall footprint to these parameters, it is essential to calculate them empirically, and to provide a measurement of the uncertainty in the value estimated.

For the period that livestock are at grass, the majority (if not the entirety) of the diet comprises grazed grass. The grazing period varies between systems and regions, and may be year-round (e.g. Cardoso et al., 2016) or seasonal (e.g. Casey & Holden, 2006; Beauchemin et al., 2010); frequently, though, it represents more than half of the year. Accordingly, estimates of these parameters for grazing land are necessary, and in the absence of dietary supplementation at pasture, directly represent the values for the diet as a whole for this period. These factors mean that the accurate parameterisation of grassland nutritional characteristics is of considerable importance to the overall footprint.

5.1.3. The biology of grassland management response

The nutritional characteristics of temperate grasses are variable between species, and grassland sward composition varies widely depending on a number of factors (Frame, 1992). The digestibility also varies across the grazing season as the individual plants enter different stages of development. The sward species composition is in itself affected by management practices (for example reseeding, fertilising, and cutting), and also varies in accordance with the age of the sward (Swift et al., 1983; Hopkins et al., 1988; Frame, 1992). Cultivation of grassland (i.e. sowing of desired species, and management of the resulting sward) is widely practised as a method to improve the nutritional quality of grassland (Frame, 1992), likely to improve grazing quality primarily through impacting species composition (Bruinenberg et al., 2002). Improved and unimproved grassland are therefore largely distinguishable based on the species composition of the sward.

Application of fertiliser to a sward, a relatively common aspect of cultivated grassland management, acts primarily to ensure that the grass plants receive adequate nutrients for growth and development, but through this can also affect the progression of sward composition over time (Hopkins et al., 1988). Biologically, faster growing species (typically those sown by the cultivator) are more likely to outcompete species adapted for slower growing species in conditions of greater nutrient availability, meaning that sown species are typically more likely to persist in fertilised swards. Application of artificial N can also suppress biological N fixation (Hungria et al., 2006), limiting the viability of leguminous species.

Aside from variability in sward composition, digestibility in an individual plant also varies across the grazing season (Frame, 1992). Young stems and leaf sheaves are highly digestible, but as these age and lignify the digestibility drops. Also affecting the digestibility is the ratio of stem to leaves, with leaves, at a greater ratio of cell contents to cell wall, being more digestible (Frame, 1992). Thus, as the plant matures, the digestibility falls.

Rates and stages of growth vary between species, which leads to differences between species in the way that digestibility vary across the grazing season. The timing of reproductive growth also impacts this trajectory. The cutting and grazing regime also has considerable impact on leaf growth and consequently on digestibility (Frame, 1992). Nevertheless, a common trend is present with most species beginning the season at high digestibility and declining steadily until July, before levelling out and recovering in September and October.

In addition to responses to management practices, grass sward composition and digestibility of individual plants and species can be impacted by a number of environmental factors. Soil is responsible for the physical, biological and chemical sustenance of the grass sward, and variations in soil type, structure, composition and pH have considerable impact upon sward development and diversity (Frame, 1992). Differences in altitude, climate and temperature are also important factors. Techniques for the measurement or estimation of nutritional characteristics are also themselves imperfect (Bruinenberg et al., 2002), though the impact of this factor is relatively small in comparison to real-world variation. There consequently exists considerable uncertainty, explicable by a number of environmental, management and experimental factors, in the nutritional value of grass swards.

5.1.4. Aims and objectives

The importance of feed digestibility to the carbon footprint of beef production has been demonstrated by several studies examining the mitigation potential of improvements to cattle rations (e.g. Doreau et al., 2011; Mathot et al., 2012; Hünerberg et al., 2014). There exists, however, a lack of research into the characterisation of diets in farm-level modelling, and in particular, the role of grassland digestibility on the carbon footprint of beef production has been largely ignored by developers of farm-level greenhouse gas (GHG) models. This is an especially pertinent consideration given the extent to which the nutritional quality of grassland can vary in response to both management practices and variations in natural conditions.

As a result of these factors, this study aims to develop a modelling approach to the estimation of the nutritional quality of grazed grassland, with a focus on digestible energy percentage as one of the main factors influencing the emission of enteric methane. The aim of this approach is to provide a sound, scientific basis for estimates of grassland DE% used to parameterise beef production systems in models which utilise IPCC Tier 2 methodology (Dong et al., 2006). By necessity, the study will focus on temperate, European grasslands, with a focus on United Kingdom data; however, the defined approach aims to provide a framework which can be adapted to other climates and world regions.

5.2. Identification of source data and definition of modelling framework

5.2.1. Modelling constraints and objectives

The necessary simplicity of the AgRE Calc input represented a defining factor in the derivation of variables for the grass model. AgRE Calc is designed as a farm-level model with low data input burden, meaning input data must be available to the typical farmer or land manager (see section 1.4 of this thesis). This approach renders the application of the tool far broader than more complex models, though by necessity reduces the precision with which the tool can make predictions. The rationale for modelling the nutritional characteristics of grazing land is to improve the precision and accuracy of predictions made by AgRE Calc, but crucially without increasing data input burden to the user to the point where applicability of the model is limited.

Based on this, the model developed had to a) be flexible enough to represent the main variations in grassland nutritional characteristics, b) capture the extent of the uncertainty in the estimates and c) utilise input data already required by AgRE Calc for estimation of GHG emissions.

5.2.2. Literature review: collating estimates of grassland digestibility

The first stage in development of the approach was to collate primary data on grassland digestibility. Estimates of digestibility of grassland exist in the literature in two main forms; species-specific estimates and estimates for a mixed sward. One of the major defining factors for the digestibility of a sward is the species composition; DE% varies greatly between species (Frame, 1992). Consequently, many published measurements of grass DE% are species-specific, whilst sward-level estimates must be compared with caution if the precise spp. composition is not known.

Primarily focusing for this reason on spp. specific measurements, a comprehensive review of the available academic and industry-published literature was performed to identify and collate grass DE% measurements (or corresponding metrics) taken by previous studies. In addition to spp. specific measurements, a number of sward-level estimates were identified, and collated alongside the main data. The results of this review are summarised in Table 5.1 and presented in full in table appendix section A.5 (table A.6).

Table 5.1. Number of digestible energy measurements extracted from the literature by species and source.

	Individual species																	Mixed	
	Lolium. perenne	Trifolium repens	Dactylis glomerata	Phleum pratense	Poa pratensis	Poa trivialis	Agrostis stolonifera	Agrostis capillaris	Elymus repens	Holcus lanatus	Ranunculus repens	Rumex acetosa	Alopecurus geniculatus	Festuca rubra	Anthoxanthum odoratum	Nardus stricta	Molinea caerulea	Pasture	Pasture w/ clover
Armstrong et al. (1989) in Bruinenberg et al. (2002)	3	2														2	2		
Buske (pers. comm.) in Bruinenberg et al. (2002)					1	1	1		1	1	1	1	1						
Dale et al. (2008)																		21	
Frame & Laidlaw (2011)																		9	9
Frame (1991) in Bruinenberg et al. (2002)	2				2		2	2		2				2	2				
Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)	2					2	2			2			2						
Korevaar (1986) in Bruinenberg et al. (2002)	2				2	1	2	2	2	2	2	2							
Terry & Tilly (1964) in Bruinenberg et al. (2002)	3	3	3	3														3	
TOTALS	**12**	**5**	**3**	**3**	**5**	**4**	**7**	**4**	**3**	**7**	**3**	**3**	**3**	**2**	**2**	**2**	**2**	**33**	**9**

5.2.3 Definition of modelling approach

With this literature survey as the primary source for the development of a modelling approach to DE% estimation for grassland, the following approach was defined:

Fixed variables, to be accounted for through model inputs, were defined as follows:

- **Grassland type;** defined in AgRE Calc as improved or unimproved
- **Grazing season;** defined in the AgRE Calc input as the time, in months, that cattle are at grass
- **Sward age/rotation period;** defined in years in the AgRE Calc input; this is an existing input used in GHG modelling to scale calculations of crop residue emissions (de Klein et al., 2006)
- **Nitrogen fertiliser application rates;** defined in kg ha^{-1} in AgRE Calc, used in GHG modelling to calculate N_2O emissions from artificial nitrogen (de Klein et al., 2006)

This chapter describes the rationale and approach to the derivation of an estimated DE% for grassland based on the modelling inputs detailed above. The basic structure of model for grazing land was defined as shown in Fig. 5.1.

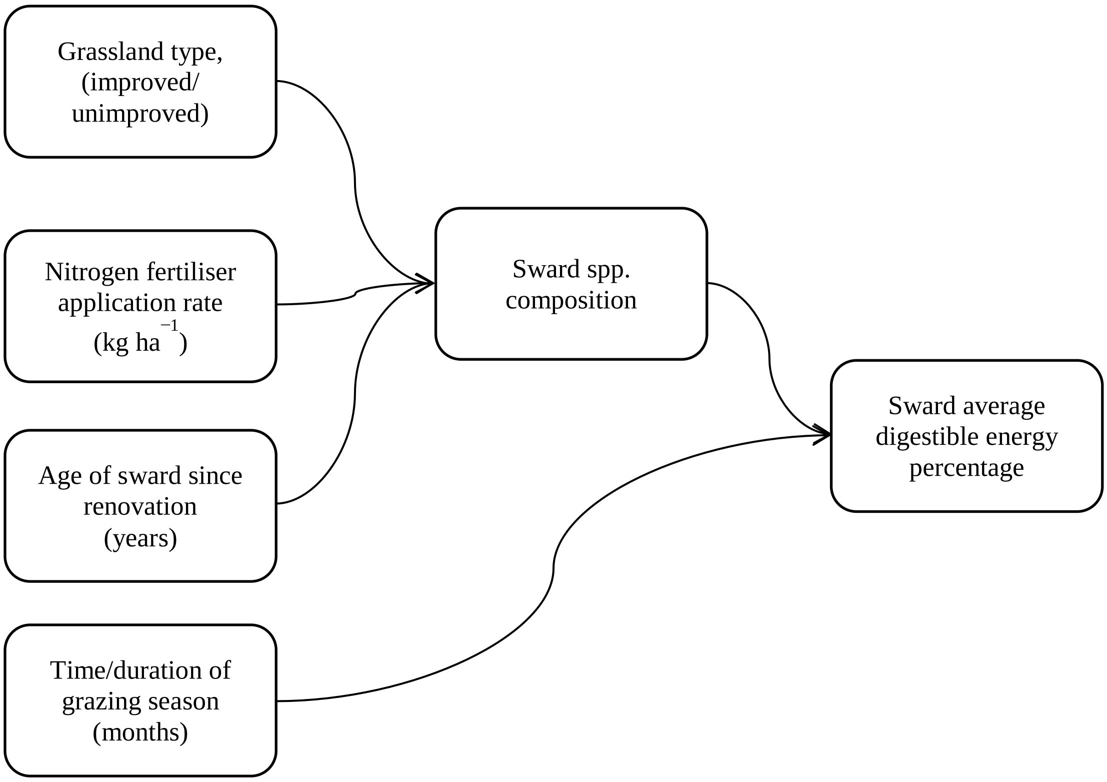

Fig. 5.1. Basic structure of data processing for grazing land digestible energy model.

Based on the approach defined in section 5.2.1, uncertainty surrounding estimates of DE% had to be accounted for by the model. It was therefore determined that uncontrolled (uncertain) variables would be accounted for in the model through Monte Carlo estimation of uncertainty. These uncontrolled variables were defined as:

a) Intra-specific uncertainty in DE%. This could stem from either genuine variation in the digestibility measurements of a particular species, or from uncertainty in the accuracy of those measurements (Bruinenberg et al., 2002).

b) Uncertainty in the change in digestibility across the grazing season. Data from the literature is of sufficient quality to map the change in digestibility across the grazing season, though there are variations within this trend. These are likely to be representative of a) inter-annual climatic variability, b) geographical variability, c) uncertainty in measurement accuracy and d) variations in sward spp. composition.
c) Uncertainty in the spp. composition of grassland. Whilst the species potentially present in grazing were defined based on model inputs, there is likely to be a) uncertainty in the translation of these inputs into actual spp. composition of the grazing land and b) variability in the relative concentrations of these species types in the sward.

The development of the Monte Carlo simulation used to characterise the uncertainty surrounding these variables, and quantify its impact on model output, is described in full in section 5.3.3.

5.2.4. Defining improved vs. unimproved grassland

Managed grasslands can be broadly split into two categories; improved and unimproved (Frame, 1992). Improved grasslands are periodically renovated through re-sowing of certain, favoured species, and are likely to be more intensively managed. Unimproved grasslands contain unsown grasses only. The motivation for renovating grassland in this way is largely related to animal performance; sown species are typically selected for high productivity and digestibility (Frame, 1992).

As a result, these two grassland types are largely distinguished by the sward spp. compositions. This study follows this approach; this is possible given the availability of published digestibility measurements relating to specific species. Based on a review of both academic (Terry & Tilley, 1964; Bruinenberg et al., 2002; Frame & Laidlaw, 2011; INRA, 2012) and industry-published literature (Dale et al., 2008; Hybu Cig Cymru, 2008; Germinal, 2015), sown and unsown species were defined as shown in table 5.2.

Table 5.2. Classification of grassland species for which published data was available.

	Species	Common name
Sown	*Lolium perenne*	Perennial ryegrass
	Trifolium repens	White clover
	Dactylis glomerata	Cocksfoot grass
	Poa pratense	Timothy grass
Unsown	*Poa pratensis*	Common meadow grass
	Poa trivialis	Rough meadow grass
	Ranunculus repens	Buttercup
	Agrostis stolonifera	Creeping bent
	Agrostis capillaris	Common bent
	Elymus repens	Couch grass
	Holcus lanatus	Yorkshire fog
	Rumex acetosa	Sorrel
	Alopecurus geniculatus	Water/marsh foxtail
	Festuca rubra	Creeping red fescue
	Anthoxanthum odoratum	Sweet vernal grass
	Neocollyris stricta	Matgrass
	Molinea caerulea	Purple moor grass

As might be expected, more research focus is aimed at improved pasture land, usually with an aim to assess and guide the effects of management intervention. Consequently, detailed accounts of spp. composition for improved pasture are much more readily available than that for unimproved pasture. However, based upon the literature cited above, it was decided to classify unimproved grazing land as consisting entirely of unsown species (as defined in table 5.2). Improved grazing land would consist of a mix of sown and unsown species, with the exact proportions of this defined by two further factors; sward age and application rate of nitrogen fertiliser. The process for defining this is described in section 5.3.2.

It is worth noting at this stage that most improved grazing land is likely to contain primarily one sown species (i.e. the one which has been deliberately cultivated). However, input parameters for AgRE Calc do not contain this data, and so to account for this it is necessary to assume a mix of sown species. Section 5.2.3 describes the derived method for defining the sown and unsown spp. mix in improved pasture.

5.3. Development of modelling approach

5.3.1. Defining a temporal digestibility trajectory over the grazing season

As discussed in section 5.1.3, biological development of the grass plants within a sward result in changes to sward digestibility across the grazing season. Given that AgRE Calc already collects input data required to characterise the period at grass, it was determined that the digestibility model should attempt to take account of this transition. Within the sampled literature (section 5.2.2), four sets of data existed with enough temporal completeness to examine change in DE% across a grazing season. These data were from Frame (1992) (one dataset) and Dale et al. (2008) (three datasets). These data are represented graphically in Fig. 5.2a.

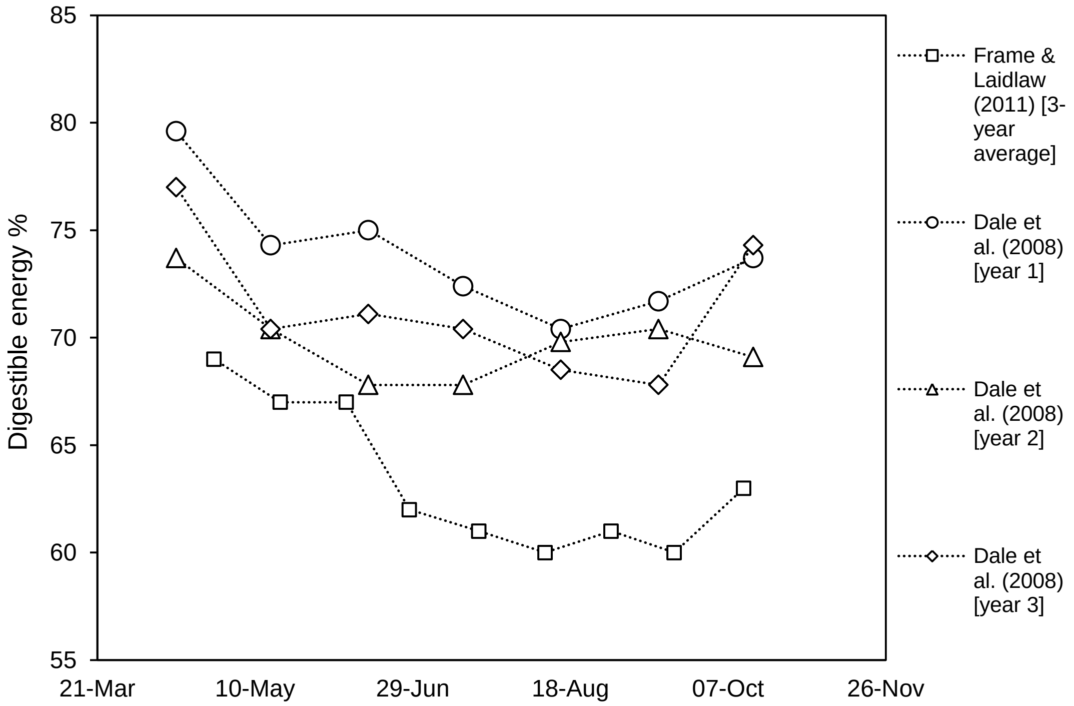

Fig. 5.2a. Graph showing intra-annual trends in DE% as sampled from the published literature.

Fig. 5.2a shows a relatively clear pattern of declining DE% in the first part of the grazing season, followed by a recovery towards the end. This is consistent with written accounts in the published literature (Bruinenberg et al., 2002; Frame & Laidlaw, 2011). Fig. 5.2a also shows some systematic differences, indicative of differences in pasture quality, between the data published by Dale et al. (2008) and that published by Frame & Laidlaw (2011). There is also some difference between the average annual values published by Dale et al. (2008); unfortunately, it was not possible to access the original data used by Frame & Laidlaw (2011) to calculate the published three-year average, but it can reasonably be assumed that inter-annual variability was likely similar to that experienced by Dale et al. (2008).

At this stage the data from Frame & Laidlaw (2011) was also temporally standardised, so that the measurements, which were taken on 21-day intervals, were converted to monthly measurements comparable with both the data from Dale et al. (2008) and the model input data. This process followed a weighted-average approach and is summarised graphically in Fig. 5.2b.

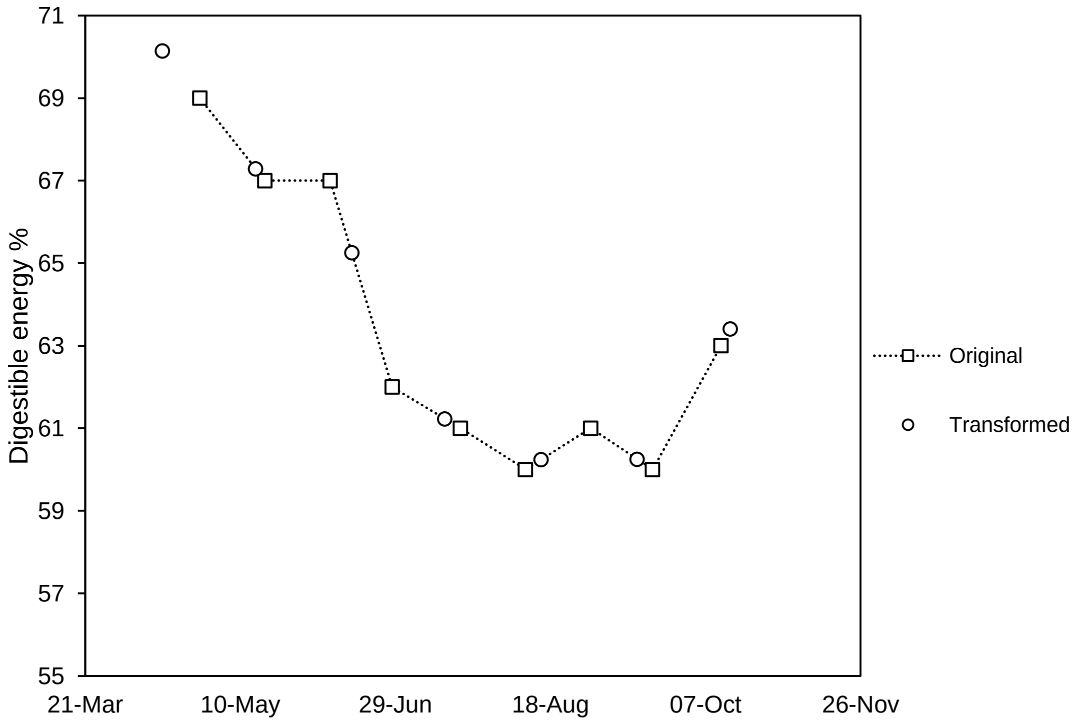

Fig. 5.2b. Temporal transformation of dataset from Frame & Laidlaw (2011). Some extrapolation was necessary at both ends of the dataset; however, the continuation of these trends was strongly supported by available data (Tilley & Terry, 1963; Dale et al., 2008).

Since the objective of this methodological section was to isolate seasonal trends, the next stage was to standardise the published values based on the overall annual average for each set of measurements. This removed any inter-system or inter-annual variability, rendering the seasonal trends in the data directly comparable, and is referred to in the following analyses as the DE% baseline. Additionally, having controlled for these systematic differences, the remaining variation isolated in the dataset can be attributed to uncertainty in the seasonal trend in DE% as well as any measurement uncertainty. This is to be accounted for through Monte Carlo simulation (see section 5.3.3).

An additional methodological decision required at this stage was whether or not to assume that differences in uncertainty across the season were significant, i.e. whether to separately calculate measures of variance for each set of monthly measurements, or whether to combine these into an overall monthly average value. These monthly variances were not wholly inconsistent and b) the variances appeared to show a trend of increase as the season progressed, which could conceivably represent the compounding effect of differing environmental or management variables. Whilst it is acknowledged that the dataset is too small to draw definite conclusions from the latter observation, it makes logical sense, as climatic and management variation will have increasing influence with further progression into in the season. Based on this intuition, it was determined to model the monthly variances separately, according to the data, rather than to amalgamate them into an average monthly variance.

An additional challenge was present in that no background data was available for the three-year average published by Frame & Laidlaw (2011). It was therefore assumed that the month-by-month inter-annual variation present in this data would have been similar in magnitude to that shown in the three separate annual datasets published by Dale et al. (2008).

To obtain a measure of this, the standard deviation for DE% baseline month-by-month was obtained for the annual datasets, and this was used to calculate the monthly relative standard deviation (*RSD*). The monthly *RSD* was then used to estimate a month-by-month standard deviation for the three-year average dataset. The standard deviations for both were then combined to create an overall measure of the data variability. With two samples of equal size (3 years), the formula for pooled standard deviation (IUPAC, 1997) could be simplified to the following (eq. 5.1):

Equation 5.1. Calculation of combined standard deviation for annual digestibility baselines.

$$S_c = \sqrt{\frac{{S_1}^2 + {S_2}^2 + (\bar{x}_1 - x_c)^2 + (\bar{x}_2 - \bar{x}_c)^2}{2}}$$

Where:
S_c = combined standard deviation
S_1 = standard deviation for sample 1
S_2 = standard deviation for sample 2
$\bar{x}_c$ = overall mean
$\bar{x}_1$ = mean for sample 1
$\bar{x}_2$ = mean for sample 2

Eq. 5.1 was used to calculate the combined standard deviation for the overall sample, month-by-month. For the combined average, the means for each 3-year dataset were weighted equally. Fig. 5.3 presents an overall average trend together with calculated overall standard deviations.

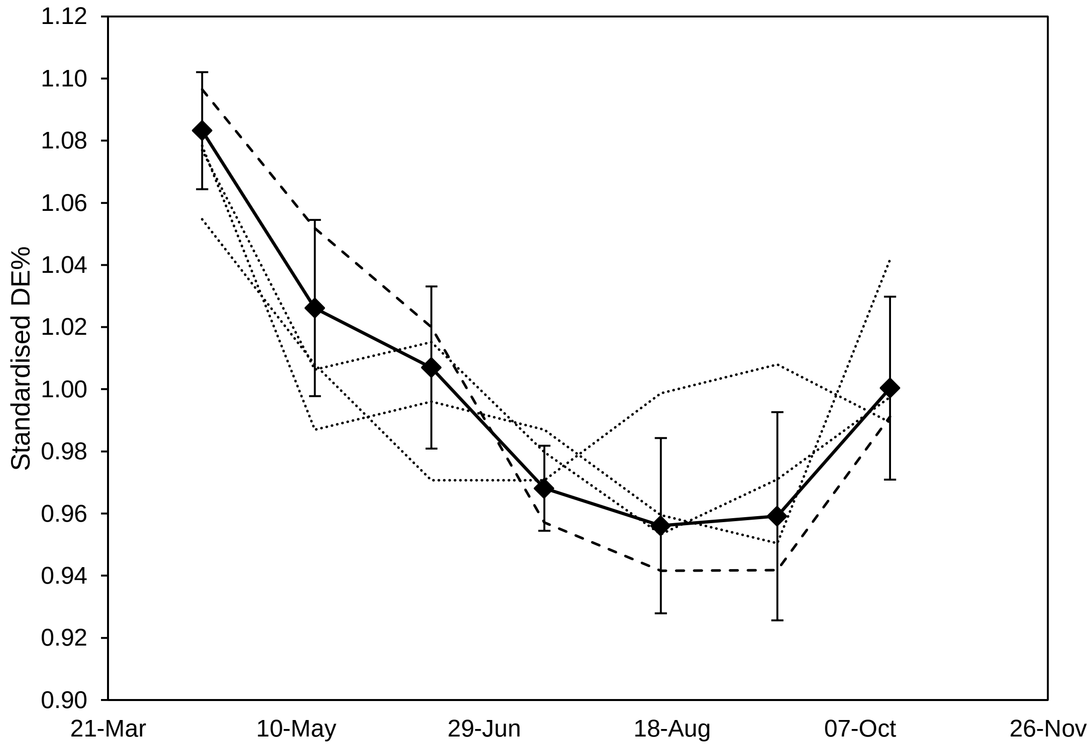

Fig. 5.3. Final calculated average trend for DE% across the grazing season. Dotted/dashed lines behind the main trend show original datasets; note that the dashed line is a 3-year average, so has 3x leverage on the overall average compared to the three annual measurements (dotted lines). Error bars show ±1 standard deviation as calculated.

5.3.2. Defining proportion of sown to unsown species in relation to sward age and N application rate

As a sown sward ages, repopulation by native species occurs. The rate of this transition is likely to depend upon a number of environmental factors, the relative importance of which will also vary depending on the biology of the grass species in question (Frame, 1992). However, with these factors constant, the stage of the transition is likely to correspond proportionally to the age of the sown sward. Consequentially, it makes sense to include a measure of sward age since renovation as an explanatory variable for species composition. This approach is supported by the results of several previous studies (Forbes et al., 1980; Swift et al., 1983; Hopkins et al., 1988), which all showed a linear relationship between sward age and species composition.

Many of the environmental factors which impact the rate of this change fall outside the scope of this modelling approach. This is due both to constraints in available data and in available model inputs and further compounding the issue is the fact that many such factors will impact differently on swards of differing species composition. However, studies observe that the majority of sown species respond similarly to soil nitrogen availability (Frame, 1992; Bruinenberg et al., 2002), with increasing levels of available nitrogen allowing the typically more productive sown species to maintain a higher presence in the sward. Nitrogen availability depends on a number of factors, not least of which being previous crop rotations (Frame, 1992). However, in the absence of the necessary information to perform a fuller estimation of available soil nitrogen, and because application rates of fertiliser N was available in the base data and as an AgRE Calc input, it chosen as a proxy variable to estimate this factor.

From a survey of the academic literature, two datasets were identified that provided enough detail to enable a modelling approach to predict the response of sown grass and legume species to sward age and N application. These datasets were published by Swift et al. (1983) and Forbes et al. (1980). The data sources are summarised in table 5.3, and raw data is presented in appendix section A.5 (table A.7).

Table 5.3. Datasets chosen for main analysis.

Author/date	Survey years	Survey area	Number of observations
Swift et al. (1983)	1974 - 1978	England and Wales	85
Forbes et al. (1980)	1976 - 1978	Eastern Scotland	121

Both data sources (Forbes et al., 1980; Swift et al., 1983) provided observations of the following variables:

a) Proportional ground cover of sown spp. in the sward. Forbes et al. (1980) termed these ‘preferred species’, but both studies agreed with the classifications defined in table 2.
b) Proportional ground cover of white clover (*T. repens*) in the sward.
c) Age of the sward, in years. Forbes et al. (1980) presented this in the form of an age index, which was back-translated into years. The method for this is detailed in appendix section A.6.
d) Nitrogen application rate, in kg ha^{-1} yr^{-1}.

The aim of this approach was to develop a multiple regression model (Lai et al., 1979) which accounted for both predictor variables. The first stage in development of this model was to examine the relationship between these parameters individually. As the most commonly cultivated legume species, both datasets provided separate data on *T. repens* abundance; given that leguminous species are likely to respond differently to nitrogen availability compared to grass species, (Frame, 1992), it was determined *T. repens* abundance should be modelled separately. The proportion of sown grass spp. was therefore calculated by subtracting *T. repens* abundance from the overall sown spp. density. Presence of other legume species, such as red clover, was considered negligible based on conclusions from Swift et al. (1983) and Hopkins et al. (1988). To explore the interactions, trends in sward spp. composition based upon sward age (i.e. time since re-sowing) were firstly examined in the absence of influence from N application rates. Fig. 5.4 (below) shows original data as published by both sets of authors (Forbes et al., 1980; Swift et al., 1983).

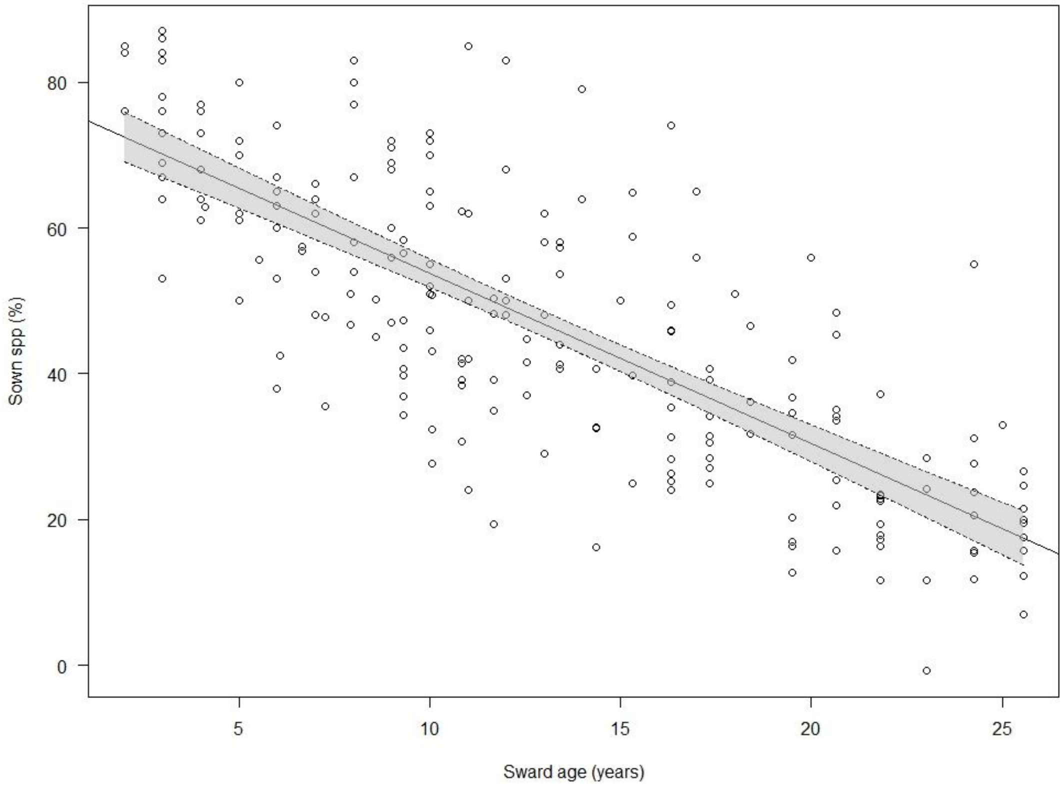

Fig. 5.4. Sown species density data in comparison to sward age. Datasets from Forbes et al. (1980) and Swift et al. (1983). OLS linear model provides a significant fit (R^2 = 0.598, p < .0001). $y = (-2.33 \pm 0.13)x + (77.14 \pm 1.96)$. Dotted lines show 95% C.I. for model fit.

Fig. 5.4 shows a relatively strong negative correlation; this was backed by the interpretation of this data by both sets of authors (Forbes et al., 1980; Swift et al., 1983) and by the discussion of the subject by Frame & Laidlaw (2011). It is worth noting that a linear model for this scenario must have some limits, as neither variable can be negative; additionally, it seems logical that whilst sown spp. density may approach zero as the sward ages, it should not intersect with the *x*-axis. However, in recognition of the scope within which the model as a whole is designed to function, a linear relationship was chosen to represent this interaction.

The next stage in development of a predictive model for the data was to explore the effects of nitrogen fertiliser (N) application rate in isolation (Fig. 5.5).

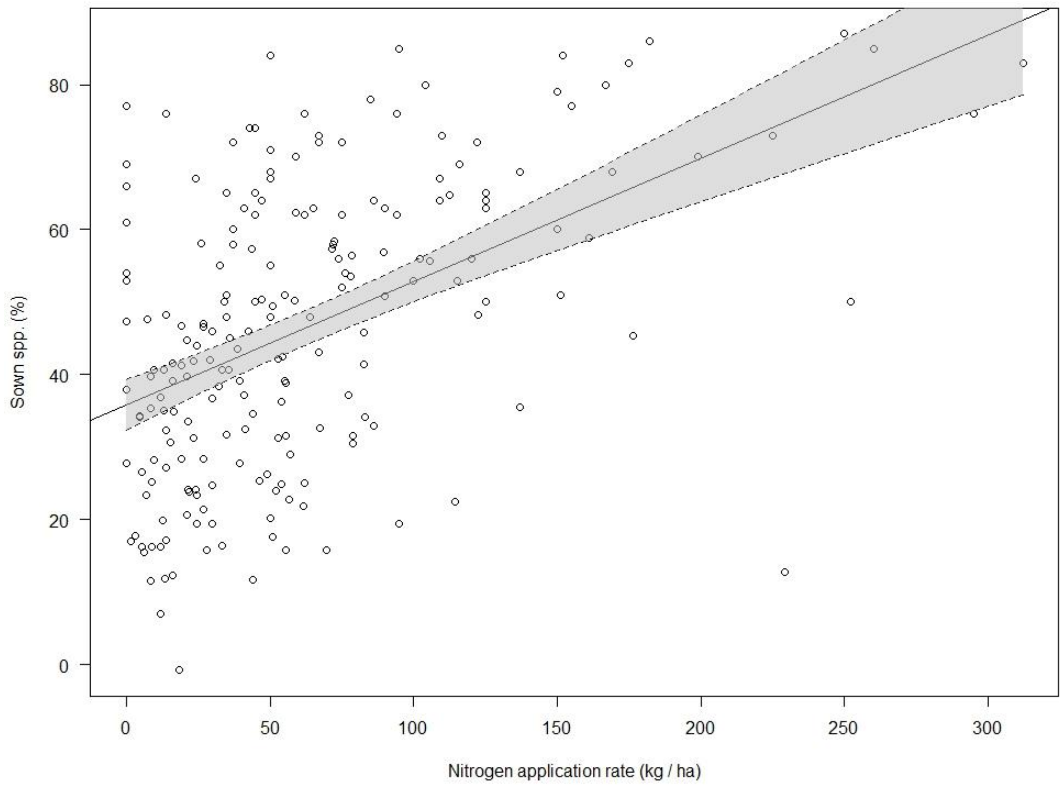

Fig. 5.5. Sown species density data in comparison to nitrogen application rate. Datasets from Forbes et al. (1980) and Swift et al. (1983). OLS linear model provides a significant fit (R^2 = 0.252, p < .0001). $y = (0.17 \pm 0.02)x + (35.84 \pm 1.76)$. Dotted lines show 95% C.I. for model fit.

Though demonstrating a weaker effect than sward age, nitrogen application rate was identified as significant predictor of variability in sown spp. density. A positive correlation was expected here; higher soil nitrogen availability was identified in the literature (Frame, 1992; Bruinenberg et al., 2002) as typically favouring sown over unsown species. The results of this analysis suggest that nitrogen application rates to soil are an acceptable proxy variable to capture this interaction.

A linear model described relatively low correlation between the predictor variables (R^2 = 0.097, p < .0001) and plots revealed no evidence of a non-linear relationship. Given these considerations, no interaction was assumed for the model. Based on this exploration of the available data, a multiple linear regression model was fit to the dataset, utilising sward age and N application rate as predictor variables. The model fit was significant (F = 210.3 on 2 and 208 DF, p < 0.001) and the model explained 67.5% of variation in the data. Full model statistics are presented, following model integration, in the following section (Table 5.6a).

Several sources (Forbes et al., 1980; Swift et al., 1983; Frame, 1992; Bruinenberg et al., 2002) identified perennial ryegrass (*Lolium perenne*) as a highly prominent member of sown swards. It was determined that, if possible, this factor should be represented in the development of the model. Hopkins et al. (1988) published data distinguishing *L. perenne* from other sown spp. across varying sward ages and corresponding sown spp. densities. This data showed a highly linear trend, indicating that the relative proportion of *L. perenne* to other species in the sown sward remains constant as the sward ages and reduces in sown spp. density. As a result of linearity of this trend, it was determined that *L. perenne* density would be estimated as a direct proportion of modelled sown spp. density. Calculation of this parameter using the collated data from Swift et al. (1983) found that *L. perenne* forms on average 82.22 ± 3.08% of the sown grass sward ($N = 85$).

Both datasets used in the development of the model (Forbes et al., 1980; Swift et al., 1983) provided separate data on density of white clover (*Trifolium repens*) in the sward. A separate regression model was therefore defined to allow the prediction of *T. repens* density in the sward.

In plotting *T. repens* density (as % of sward ground cover) against sward age (in years), it was found that this variable responded to the predictor in a similar manner to sown grass species. An OLS linear regression showed *T. repens* density declined with sward age ($F = 85.47$, $R^2 = .292$, $p < .00001$).

Nitrogen application rate was added to this model as a second predictor. No interaction between predictor variables was assumed (Pearson's $r = -0.319$). Addition of this second predictor variable increased the model's predictive ability over that of the simple OLS linear regression ($F = 46.53$, $R^2 = .308$, $p < .0001$).

5.3.3. Final model integration and Monte Carlo development

The first stage of integrating the model was to develop the Monte Carlo distributions to be employed in the standardised temporal DE% trajectory. Based on the above analyses (section 5.3.1) and available data it was determined that a normal distribution should be employed to characterise variability in the baseline values on a month-by-month basis. Table 5.4 (below) displays the values used to parameterise these distributions.

Table 5.4. Mean (μ) and the standard deviation (σ) for normal distributions used to characterise the standardised monthly DE% values.

	Parameters	
	μ	σ
April	1.083	0.019
May	1.026	0.028
June	1.007	0.026
July	0.968	0.014
August	0.956	0.028
September	0.959	0.034
October	1.000	0.029

This approach satisfactorily accounted for variability on a per-month basis. However, complicating the issue is the fact that the DE% baseline throughout the season is linked, i.e. the most likely values for one particular month depend to a great extent on the values for the previous month, necessitating the linking of the monthly distributions using a copula (Fantazzini, 2009). A Frank copula was chosen for this purpose, as it is unique in exhibiting no correlative change throughout its range; this was deemed to best represent the present scenario.

In order to define the strength of the copula, it was necessary to explore the consistency of the month-by-month DE% trajectory as exhibited by the sample data. For this approach, the standardised mean monthly values (table 5.4) were used as a predictor variable for the three available monthly datasets (Dale et al., 2008). This isolated the trajectory shape from other aspects of the variability, enabling assessment of the extent by which the month-by-month variation for a particular year deviated from the average trajectory (Fig. 5.6)

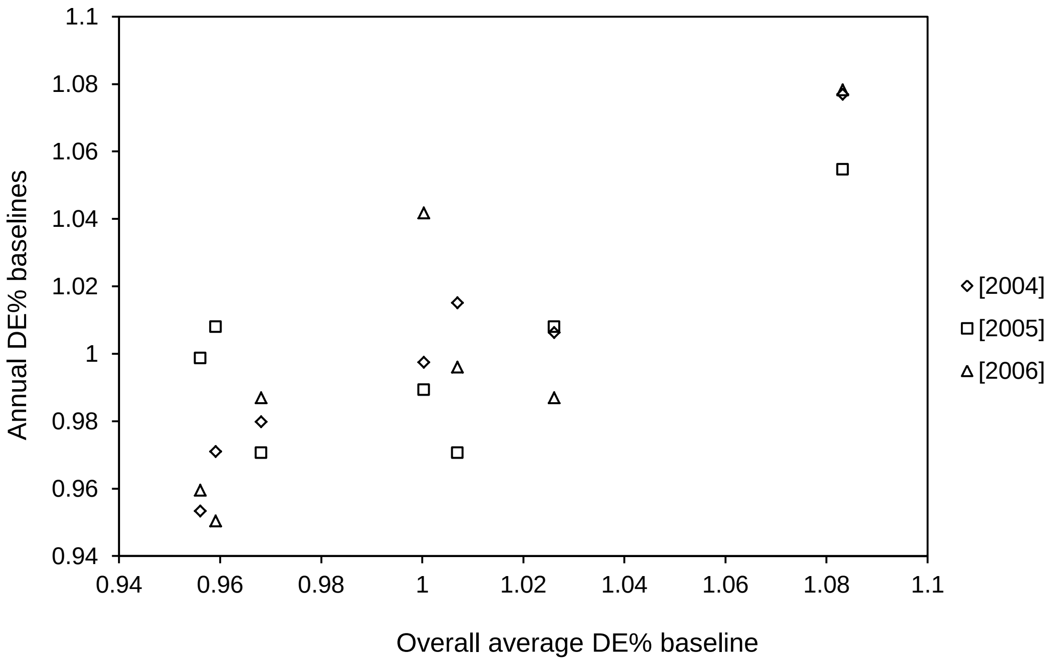

Fig. 5.6. Graph plotting standardised monthly datasets (Dale et al., 2008) against the average monthly DE% trajectory. The plot explores the extent to which the overall average acts as a predictor for the individual annual trends and allows a measure of the strength of the trend overall.

A linear model was fitted to each of the three data series plotted in Fig. 5.6. Theoretically, if the annual trend was absolutely consistent (even if absolute values varied), the R^2 value should be 1 for each model; if the annual trend was non-existent, the linear model's explanatory power should be very low. The R^2 values were 0.94, 0.45 and 0.71 ($M =$ 0.70) for the 2004, 2005 and 2006 models respectively, indicating a moderate consistency for the annual trajectory.

The parameter which defines the correlation strength for a Frank copula (θ) is scaled from between zero and 35, with zero indicating no correlation and 35 the maximum possible correlation. The mean R^2 value (0.70) was used to scale the θ value for the Frank copula, resulting in a value of 24.54 (35 × 0.70).

In order to temporally standardise the DE% measurements from the literature (table 5.1), each of the single spp. DE% measurements collated from the literature was assigned a standardised baseline value, based on the temporal trajectory defined in section 5.3.1 and the timing of the individual measurement (see table A.6 for raw data including timing of measurement). For monthly measurements, this was done based upon the distributions defined in table 5.4; if a value was an annual average, it was automatically assigned a baseline value of 1. Each measurement was then divided by its initial baseline to convert it to a pseudo-annual average measurement, controlling for the effects of temporal variability in the raw data.

The standardised measurement was then, using the same distribution set, converted to a series of 7 monthly values, providing the base data from which to calculate an average monthly sward DE%, weighted by the fractions of each species in the sward.

Sward species assemblages were then defined using the methods derived in section 5.3.2. Table 5.5a shows the species classifications defined in section 2.4, alongside a summary of the calculations derived in section 5.3.2. Table 5.5b provides interpretation of the coefficients represented in table 5.5a.

Uncertainty in the modelled species densities was characterised assuming a normal distribution for model residuals. It was determined that there would be two levels at which this could be applied; the first would apply should this model be used to make predictions at a national or regional level, and with the geographical and management-related variation this implies, would therefore account for all the unexplained variation in the original dataset. For this approach, the standard deviation of the parameter distribution was based on the calculated regression prediction interval (eq. 5.2), encompassing the full uncertainty in prediction of this parameter. Tables 5.6a and 5.6b present the values required for this calculation, together with the initial raw dataset (table A.7).

Equation 5.2. Calculation of prediction intervals for modelled scenarios (Geisser, 1993).

$$\hat{y}_h \pm t_{(\alpha/2,n-2)} \cdot \sqrt{MSE\left(1 + \frac{1}{n} + \frac{(x_h - \bar{x})^2}{\sum(x_i - \bar{x})^2}\right)}$$

Where:
$\hat{y}_h$= fitted value
$t_{(\alpha/2,n-2)}$= t-multiplier (with n−2 degrees of freedom)
MSE = mean square error of prediction
$\bar{x}$ = mean value of x variable
x_i = std. dev. of x variable

x_h = predictor (x) value
n = number of values in dataset

The second approach would apply where the model would be used to make predictions at the level of a single enterprise; as expounded in sections 5.2.1 and 5.2.2, temporal and spatial variability accounts for much of the unexplained variability in the dataset, which would not be present for a single farm-level scenario. As such, to remove the confounding effect of this variability, for farm-level scenarios, the confidence intervals of the regression model would be used to scale the modelled uncertainty, in place of prediction intervals (eq. 5.3).

Equation 5.3. Calculation of confidence intervals for modelled scenarios (Geisser, 1993)**.**

$$\hat{y}_h \pm t_{(\alpha/2,n-2)} \cdot \sqrt{MSE\left(\frac{1}{n} + \frac{(x_h - \bar{x})^2}{\sum(x_i - \bar{x})^2}\right)}$$

Where:
$\hat{y}_h$= fitted value
$t_{(\alpha/2,n-2)}$= t-multiplier (with n−2 degrees of freedom)
MSE = mean square error of prediction
$\bar{x}$ = mean value of x variable
x_i = std. dev. of x variable
x_h = predictor (x) value
n = number of values in dataset

As described in section 5.2.4, unimproved grazing land was deemed to consist entirely of unsown species. Therefore, for unimproved land, $Frac_{unsown}$ would be equal to one. Where the grazing land is classified as improved, the model described in tables 5.4, 5.5, 5.6a and 5.6b would be used to calculate the average proportions of the species groups (*L. perenne*, *T. repens*, other sown spp. and unsown spp.) present in the sward.

Table 5.5a. Classification of sown and unsown species alongside calculations of proportional sward density for improved grazing land.

	Species	Proportion in sward
Sown grasses	*L. perenne*	$Frac_{sown} = [a_1 \times S_{age} + b_1 \times N_{rate} + c_1]/100$
	D. glomerata	$Frac_{lolium} = Frac_{sown} \times Lolium\ \%$
	P. pratense	$Frac_{other} = Frac_{sown} - Frac_{lolium}$
Sown legumes	*T. repens*	$Frac_{trifolium} = [a_2 \times S_{age} + b_2 \times N_{rate} + c_2]/100$
Unsown species	*P. pratensis*	$Frac_{unsown} = 1 - Frac_{sown}$
	P. trivialis	
	R. repens	
	A. stolonifera	
	A. capillaris	
	E. repens	
	H. lanatus	
	R. acetosa	
	A. geniculatus	
	F. rubra	
	A. odoratum	
	N. stricta	
	M. caerulea	

Table 5.5b. Modelling coefficients, descriptions and units as defined in table 5.5a.

	Model coefficient	Description
Input	S_{age}	Sward age since reseeding, in years
	N_{rate}	N fertiliser application rate, in kg ha^{-1}
Intermediate	*Lolium %*	Calculated fraction of *L. perenne* in sown grasses, equal to 0.822 ± .031 *S.D* (see section 5.3.2)
Output	$Frac_{lolium}$	Fraction of *L. perenne* in sward
	$Frac_{sown}$	Fraction of sown spp. in sward (inc. *L. perenne*)
	$Frac_{other}$	Fraction of other sown spp. in sward (not including *L. perenne*)
	$Frac_{trifolium}$	Fraction of *T. repens* in sward
	$Frac_{unsown}$	Fraction of unsown spp. in sward

Table 5.6a. Model coefficients and descriptives for the multiple linear regression model predicting density of sown grass species fitted to the data. F = 210.3 on 2 and 208 DF, p < 0.0001. Residual std. error = 11.54 on 203 degrees of freedom.

	Coefficient	Std. error	t value	p value	Units
Intercept (c_1)	67.412	2.276	29.616	<.0001	%
Sward age (a_1)	−2.058	0.127	−16.165	<.0001	years / %
N app. rate (b_1)	0.097	0.014	6.817	<.0001	(kg ha^{-1} yr^{-1}) / %

Table 5.6b. Model coefficients and descriptives for the multiple linear regression model predicting *T. repens* density. F = 46.53, R^2 = .308, p < .0001. Residual std. error = 5.468 on 203 degrees of freedom.

	Coefficient	Std. error	t value	p value	Units
Intercept (c_1)	17.194	1.078	15.946	<.0001	%
Sward age (a_1)	−0.580	0.060	−9.620	<.0001	years / %
N app. rate (b_1)	−0.016	0.007	−2.377	<.05	(kg ha^{-1} yr^{-1}) / %

The regression solutions ($Frac_{lolium}$, $Frac_{trifolium}$, $Frac_{sown}$ and $Frac_{unsown}$) were bounded in the model to ensure that they could not fall outside the range 0 – 1, though this was a remote possibility even at extrapolated extremes of the model operation e.g. swards of >45 years. For $Frac_{other}$ and $Frac_{unsown}$, the ratio of individual spp. within these groups was also treated as a Monte Carlo variable. A uniform distribution of equal range was selected for each spp. density estimate, with the total of the random values subsequently standardised to the magnitude of the overall density value for the group. As a result, whilst some variation occurs, the most likely range of values is an even spread of densities across the spp. range.

5.3.4. Correlating DE% across the species range

In order to ensure that the uncertainty in DE% for the sward as a whole was represented correctly, it was necessary to determine whether, and to what extent, the unexplained variation in DE% for individual spp. is correlated across the species range. This formed a refinement of the Monte Carlo simulation development described in 5.3.3, though is presented separately as it required a wholly different set of analyses to the techniques described thus far.

The approach is justified by the logic that the environmental factors which influence intra-specific variation in DE% (modelled here as uncertainty) are likely to be comparable across the species range for a modelled scenario; additionally, as environmental factors, they are likely to have similar influence on all species in a geographically and temporally similar modelled area. For example, variations in temperature, rainfall, sunlight etc. which occur as a result of seasonal or geographical variability are likely to be similar for each species in a sward on the spatial scale modelled here. While species differ in their response to environmental and climatic factors. interpretation of the literature (Frame & Laidlaw, 2011) suggests that inter-specific DE% response is likely to show some level of parity.

The approach was necessary as the DE% of each grass spp. is simulated separately in the model before being additively combined to calculate the overall DE% for the sward. Additive combination of uncertainties in this way may act to falsely reduce the uncertainty of the final result (Röös & Nylinder, 2013); where correlation exists between variation in the components of the final result, this will negate the effect of additive reduction. Accordingly, failure to account for this in the simulation may result in underestimation of the final uncertainty.

The aim of this approach was therefore to a) test the null hypothesis that the spatial and temporal specificity of a measurement has no effect on the remaining unexplained variability in DE%, and b) should the null hypothesis be rejected, to qualify and quantify in order to represent it mathematically in the modelling process. Statistical processes were carried out in R (R Core Team, 2017) and ModelRisk (Vose Software, 2013) and the acceptance level for results was set at $p < .05$.

Fig. 5.7 shows results from an initial 'proving run' of the Monte Carlo simulation (10,000 repetitions, Mersenne seed = 2605). The regression equations described in section 5.3.3 predict greater sward species diversity with age, meaning that the effects of additive combination of uncertainties increases (e.g. Röös and Nylinder, 2013). As can be seen, uncertainty in sward digestibility markedly decreases with age as a result of this. Whilst this is not necessarily incorrect, failure to examine the potential for inter-specific correlation in DE% would render the validity of this trend an unknown quantity.

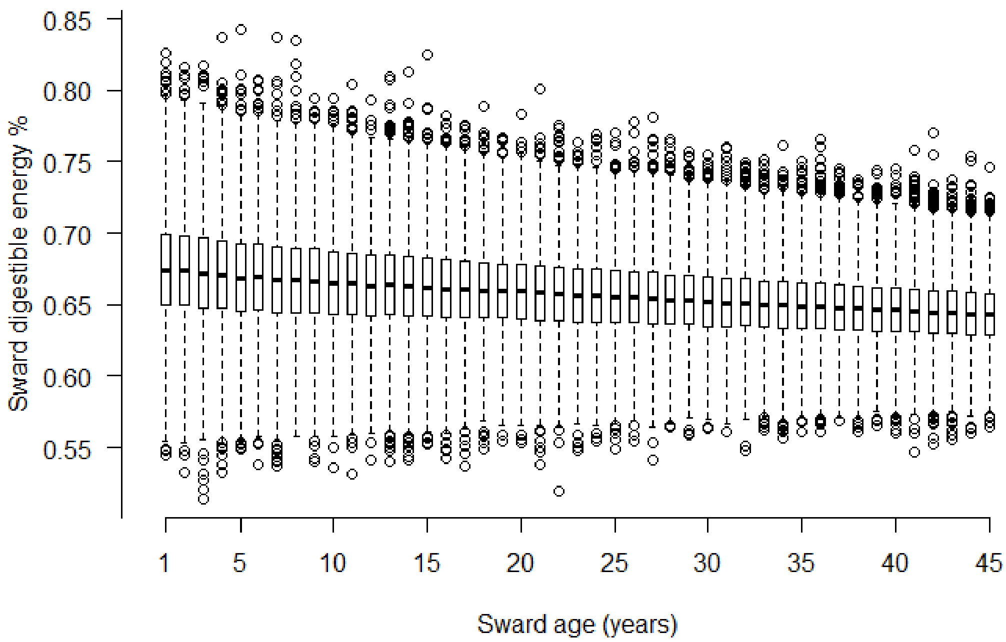

Fig. 5.7. Initial Monte Carlo simulation results. Sward digestibility decreases over time as predicted, though the decrease in uncertainty is also noticeable.

Whilst the logical argument presented above is arguably justification for the assumption of some common environmental influence, it was necessary to examine this statistically in order to include this factor in the modelling process. In order to conduct the required analyses, it was therefore necessary to factorise the raw DE% data (table 5.1) into groups which were representative of spatial and temporal parity.

In order to achieve this, a subset of the raw data was first taken from which non-spp. specific and non-temporally specific measurements of DE% were excluded. This subset was then further factorised by source author and measurement timing, resulting in the groups presented in table 5.7. The aim of this approach was isolate data into unique sample groups where observations possessed temporal and spatial parity.

Table 5.7. Main dataset as presented in table 5.1, factorised into groups representing unique sampling environments.

Sample	Sample size (n)	Timing	Source
1	4	August	Armstrong et al. (1989) in Bruinenberg et al. (2002)
2	4	June	Armstrong et al. (1989) in Bruinenberg et al. (2002)
3	5	June	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
4	5	May	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
5	8	August	Korevaar (1986) in Bruinenberg et al. (2002)
6	9	May	Korevaar (1986) in Bruinenberg et al. (2002)
7	4	April	Terry & Tilly (1964) in Bruinenberg et al. (2002)
8	4	June	Terry & Tilly (1964) in Bruinenberg et al. (2002)
9	4	May	Terry & Tilly (1964) in Bruinenberg et al. (2002)

Variability still existed in the data as a result of species and season. However, given the analyses performed in section 5.3.1, it was possible to standardise the data based upon these factors. The seasonal baseline approach developed in section 2.3 was used in order to standardise the DE% for the effects of seasonality of sample measurement. A deterministically calculated mean was employed rather than the stochastic approach described in 2.5, though in other respects, the application was identical to the model itself. Alongside this, the value for each observation in each sample was divided by the species mean for the whole group (again, deterministically).

This controlled for the effects of explained variation, i.e. the variation accounted for by the model variables. Residual variation was therefore accounted for by unexplained factors. Theoretically, if residual variation was zero, all values across the whole sample would have been standardised to a value of 1 by this process. Likewise, if the spatial and temporal specificity of the sample (hereinafter referred to as the sampling environment) had no effect on the remaining variation (i.e. should the null hypothesis prove true), there should be no difference between the means of the groups. Fig. 5.8 shows the spread of the grouped data:

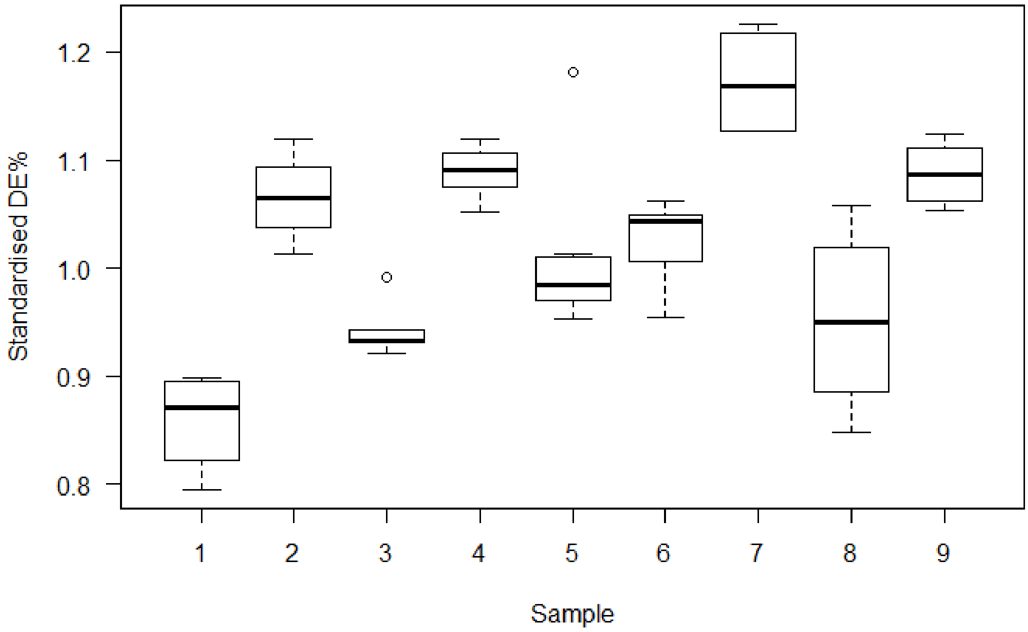

Fig. 5.8. Distribution of standardised DE% across the different sampling environment groups. See Table 5.6 for sample numbers.

A one-way ANOVA was identified to test the statistical significance of the deviation from the theoretical mean. Levene's test confirmed the assumption of homogeneity of variances (F = 0.78, p = 0.62) and the Anderson-Darling test showed no significant deviation of the data from the normal distribution (A = 0.188, p = 0.90), allowing the use of a parametric test. The ANOVA showed that the effects of sampling environment have a significant impact on the standardised DE% mean across the groups (F = 10.52, $p <$ 0.0001). The null hypothesis was therefore rejected.

Having confirmed the importance of sampling environment on the standardised DE% for the data, and accepting that this variation must remain unexplained in the model, the next step was to characterise this relationship to account for inter-specific correlation of DE% between grass species in the same modelled scenario (which assumes spatial and temporal parity). In order to do this, the next step was to plot the standardised measurements, within groups, against one another. Table 5.8 and illustrates this approach using a small dummy dataset:

Table 5.8. Variable pairings for copula fit. Note 1) the repetition of pairs across the *x*-*y* categories, creating a symmetrical dataset, and 2) the omission of within-pair repetitions (e.g. Obs. 1 – Obs. 1).

Var. (x)	**Var. (y)**
Obs. 1	Obs. 2
Obs. 1	Obs. 3
Obs. 2	Obs. 1
Obs. 2	Obs. 3
Obs. 3	Obs. 1
Obs. 3	Obs. 2

This method used a within-group approach as it was designed to capture the strength and shape of the relationship within the sample groups, the previous analyses having established the statistical significance of the sampling environment. This created a dataset which could be used to show the shape of the correlation graphically (Fig. 5.9), and which could be applied to the copula fit function in ModelRisk.

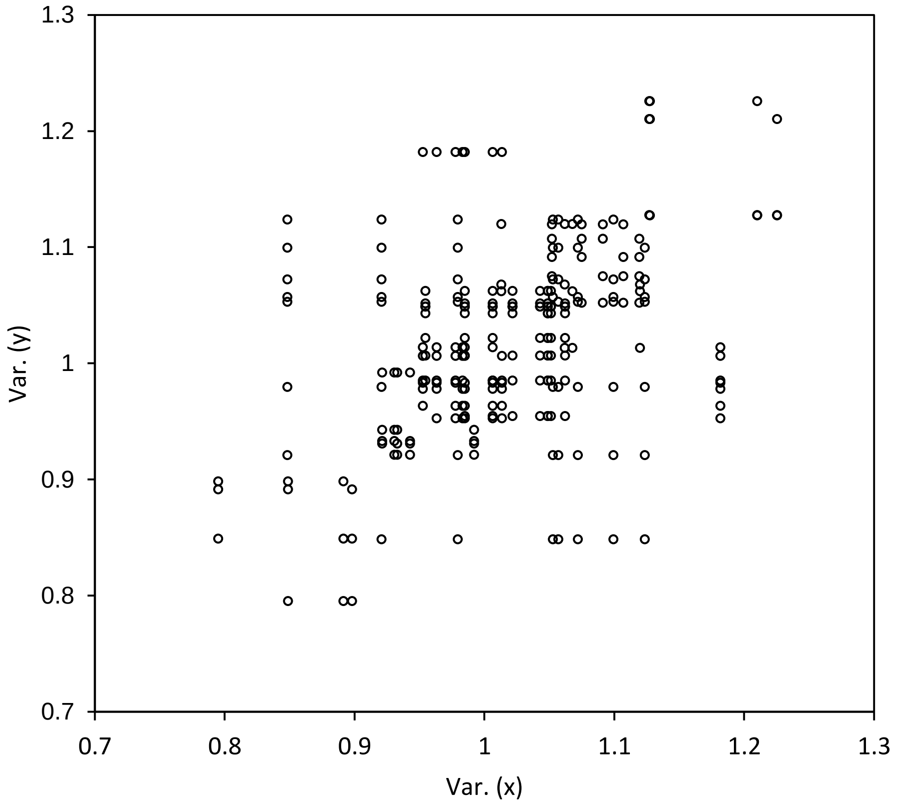

Fig. 5.9. Within-group correlation plot of standardised DE%. The dashed line ($x = y$) is shown for reference. Note the bilateral symmetry of the correlation resulting from pair repetition across the x-y categories (see Table 5.8).

From the available options, the copula fit module in ModelRisk identified a T copula as the best fit for the data (Akaike's Information Criterion = −82.99, log likelihood = 43.51). Visual appraisal confirmed that this is an appropriate choice; the T copula shows a tight correlation at low and high percentiles, remaining looser in the centre, mimicking the correlation pattern shown in Fig. 5.9. Fitted parameters were determined by ModelRisk as *Nu* = 2, *Corr.* = 0.43. Based on this assessment, the spp. DE% estimates generated by the model were linked using a T copula of the above parameters.

As in the spp. density regression models, uncertainty for the actual species-specific DE% values would be modelled in two ways; one designed to represent the full scope of the uncertainty where the model is used to consider changes at a national or regional level, and one designed to mitigate for the effects of spatial variability on the modelled uncertainty for farm-scale scenarios. Both approaches characterised uncertainty in the inter-specific DE% estimates assuming a normal distribution. For the national level model, standard deviations were calculated by species directly from the raw DE% measurements, following the temporal transformation process as described in section 5.3.1. To ensure that the uncertainty in the temporal transformation was accounted for, it was performed stochastically as described in section 5.3.3, meaning that the standard deviation as calculated by species varied to some extent in each iteration of the Monte Carlo simulation.

For the farm-scale estimation of uncertainty in intra-specific DE%, the variation resulting from both spatial and temporal variability was controlled for. The data was standardised temporally and by species, as described above for the copula fit. The process was, however, performed stochastically within the model in order to account for the effects of uncertainty within the transformations. Following this, the DE% estimates for observations within each sample group (table 5.6) were standardised by dividing by the arithmetic mean for each group.

This approach theoretically ensured that the effects of temporal variability, and variability related to the sampling environment, were accounted for in the transformed data; any remaining variation in baseline estimates for a single species represented uncertainty which should be accounted for in the farm-level application of the model. Standard deviation was calculated for each species as a percentage of the baseline values, and this was applied to the original (temporally transformed) estimates in the model.

5.4. Summary of model output

To summarise the model output for further use and analysis, a series of Monte Carlo simulations was run. Sward age and nitrogen application rate were designated as stratified input variables within the simulation, and the model was run using uncertainty parameters designed for a large-scale scenario. Sward age was defined as an integer variable with a range of 1 – 25 years, and nitrogen application rate with a range of 0 – 350 kg ha^{-1}, and a step of 25. Monte Carlo simulations of 10,000 repeats were run for each sward age and N fertilisation level (375 scenarios; 3,750,000 individual repeats. Mersenne seed = 2605) using Microsoft VBA script. Table 5.9 contains a summary of this simulation, and figures 5.10 and 5.11 present a graphical rendering of the model results.

Modelled digestible energy percentage varied from 67.2 – 71.7 (Table 5.9), with maximum digestibility observed at minimum sward age and maximum N application rate. Modelled standard deviation varied from 4.6 – 1.7, with lowest uncertainty observed where the modelled sward was most diverse. It should be noted that the modelled values are relatively high compared to some published estimates; for example, the assumed UK inventory DE% for beef cattle is 65% (MAFF, 1990; Salisbury et al., 2014). This is within modelled bounds, but lower than predicted; since modelled values are based on measured DE% values for individual grass species, this discrepancy may indicate an assumption that winter housing rations (e.g. straw) serve to pull down the average.

The following chapter of this thesis utilises this model in modelling a pasture-based extensive beef production system, and assesses the sensitivity of this approach to the output of the developed grassland digestibility model.

Table 5.9. Summary of modelled digestible energy % results of Monte Carlo simulations for grassland digestibility model developed in chapter five of this thesis.

Sward age since reseeding (years)	Nitrogen application rate (kg ha^{-1})														
	0	**25**	**50**	**75**	**100**	**125**	**150**	**175**	**200**	**225**	**250**	**275**	**300**	**325**	**350**
1	71.0 ± 3.7	71.2 ± 3.9	71.3 ± 4.0	71.3 ± 4.1	71.5 ± 4.2	71.6 ± 4.3	71.6 ± 4.4	71.6 ± 4.5	71.6 ± 4.6	71.7 ± 4.5	71.7 ± 4.6	71.7 ± 4.6	71.7 ± 4.6	71.7 ± 4.6	71.7 ± 4.6
2	70.9 ± 3.7	71.0 ± 3.8	71.2 ± 3.9	71.1 ± 4.0	71.3 ± 4.1	71.3 ± 4.2	71.5 ± 4.4	71.5 ± 4.3	71.6 ± 4.5	71.5 ± 4.5	71.6 ± 4.5	71.6 ± 4.6	71.6 ± 4.5	71.7 ± 4.6	71.5 ± 4.6
3	70.8 ± 3.6	70.9 ± 3.7	71.0 ± 3.8	71.1 ± 3.9	71.2 ± 4.0	71.4 ± 4.2	71.4 ± 4.3	71.5 ± 4.3	71.4 ± 4.4	71.6 ± 4.5	71.5 ± 4.5	71.5 ± 4.5	71.6 ± 4.5	71.5 ± 4.6	71.5 ± 4.5
4	70.6 ± 3.5	70.7 ± 3.6	70.9 ± 3.7	71.0 ± 3.8	71.1 ± 3.9	71.2 ± 4.0	71.3 ± 4.1	71.4 ± 4.2	71.4 ± 4.4	71.5 ± 4.4	71.5 ± 4.4	71.5 ± 4.5	71.6 ± 4.5	71.6 ± 4.5	71.6 ± 4.5
5	70.4 ± 3.4	70.6 ± 3.5	70.7 ± 3.6	70.8 ± 3.7	70.9 ± 3.8	71.0 ± 3.9	71.2 ± 4.0	71.3 ± 4.3	71.3 ± 4.2	71.4 ± 4.3	71.5 ± 4.3	71.5 ± 4.4	71.5 ± 4.4	71.5 ± 4.4	71.5 ± 4.5
6	70.3 ± 3.4	70.4 ± 3.4	70.6 ± 3.5	70.7 ± 3.7	70.8 ± 3.8	70.9 ± 3.8	71.0 ± 3.9	71.1 ± 4.1	71.2 ± 4.2	71.4 ± 4.3	71.3 ± 4.3	71.4 ± 4.4	71.5 ± 4.4	71.4 ± 4.4	71.4 ± 4.4
7	70.2 ± 3.2	70.2 ± 3.3	70.4 ± 3.4	70.5 ± 3.5	70.6 ± 3.7	70.8 ± 3.7	70.9 ± 3.9	71.0 ± 4.0	71.2 ± 4.1	71.2 ± 4.1	71.3 ± 4.2	71.3 ± 4.3	71.3 ± 4.3	71.4 ± 4.4	71.3 ± 4.3
8	70.0 ± 3.1	70.1 ± 3.3	70.2 ± 3.3	70.4 ± 3.4	70.5 ± 3.5	70.7 ± 3.7	70.8 ± 3.8	70.8 ± 3.9	71.1 ± 4.0	71.1 ± 4.2	71.1 ± 4.2	71.2 ± 4.3	71.3 ± 4.3	71.4 ± 4.3	71.4 ± 4.3
9	69.8 ± 3.0	69.9 ± 3.1	70.1 ± 3.2	70.1 ± 3.4	70.3 ± 3.5	70.5 ± 3.6	70.6 ± 3.7	70.8 ± 3.8	70.9 ± 3.9	70.9 ± 4.0	71.0 ± 4.1	71.2 ± 4.1	71.2 ± 4.2	71.3 ± 4.2	71.3 ± 4.3
10	69.6 ± 3.0	69.8 ± 3.0	69.9 ± 3.1	70.0 ± 3.2	70.2 ± 3.3	70.3 ± 3.5	70.4 ± 3.6	70.6 ± 3.7	70.7 ± 3.8	70.8 ± 3.9	71.0 ± 4.1	71.0 ± 4.1	71.1 ± 4.2	71.2 ± 4.2	71.2 ± 4.3
11	69.4 ± 2.9	69.6 ± 3.0	69.7 ± 3.0	69.9 ± 3.2	70.1 ± 3.2	70.2 ± 3.4	70.3 ± 3.6	70.5 ± 3.7	70.6 ± 3.7	70.6 ± 3.8	70.9 ± 4.0	70.9 ± 4.1	71.0 ± 4.1	71.1 ± 4.2	71.1 ± 4.2
12	69.3 ± 2.8	69.4 ± 2.9	69.5 ± 3.0	69.6 ± 3.0	69.8 ± 3.2	70.0 ± 3.3	70.1 ± 3.5	70.3 ± 3.5	70.5 ± 3.7	70.6 ± 3.8	70.7 ± 3.9	70.9 ± 4.0	70.9 ± 4.1	70.9 ± 4.0	71.1 ± 4.1
13	69.1 ± 2.7	69.2 ± 2.7	69.3 ± 2.9	69.5 ± 2.9	69.7 ± 3.1	69.8 ± 3.2	70.0 ± 3.3	70.1 ± 3.5	70.3 ± 3.5	70.5 ± 3.7	70.7 ± 3.8	70.7 ± 3.9	70.9 ± 4.0	70.9 ± 4.0	70.9 ± 4.1
14	68.9 ± 2.6	69.0 ± 2.7	69.2 ± 2.8	69.3 ± 2.9	69.5 ± 3.0	69.6 ± 3.1	69.8 ± 3.2	70.0 ± 3.4	70.2 ± 3.5	70.4 ± 3.7	70.4 ± 3.8	70.6 ± 3.8	70.7 ± 3.9	70.8 ± 4.0	70.9 ± 4.1
15	68.7 ± 2.5	68.9 ± 2.6	69.0 ± 2.6	69.2 ± 2.8	69.3 ± 2.9	69.4 ± 3.0	69.7 ± 3.1	69.8 ± 3.3	70.1 ± 3.4	70.1 ± 3.5	70.3 ± 3.6	70.5 ± 3.8	70.6 ± 3.9	70.7 ± 4.0	70.8 ± 4.0
16	68.6 ± 2.4	68.7 ± 2.5	68.8 ± 2.6	69.0 ± 2.6	69.1 ± 2.8	69.3 ± 2.9	69.5 ± 3.0	69.7 ± 3.2	69.9 ± 3.3	70.1 ± 3.4	70.3 ± 3.6	70.3 ± 3.7	70.5 ± 3.8	70.5 ± 3.9	70.7 ± 3.9
17	68.4 ± 2.3	68.5 ± 2.4	68.6 ± 2.5	68.8 ± 2.6	68.9 ± 2.7	69.1 ± 2.9	69.3 ± 3.0	69.5 ± 3.1	69.7 ± 3.2	69.9 ± 3.4	70.1 ± 3.6	70.2 ± 3.6	70.4 ± 3.8	70.5 ± 3.8	70.6 ± 3.9
18	68.2 ± 2.3	68.3 ± 2.3	68.5 ± 2.4	68.6 ± 2.5	68.8 ± 2.6	69.0 ± 2.7	69.1 ± 2.9	69.3 ± 3.0	69.5 ± 3.2	69.7 ± 3.3	69.9 ± 3.4	70.1 ± 3.6	70.3 ± 3.7	70.4 ± 3.7	70.5 ± 3.8
19	68.1 ± 2.2	68.2 ± 2.2	68.2 ± 2.3	68.5 ± 2.4	68.6 ± 2.5	68.8 ± 2.6	69.0 ± 2.7	69.1 ± 2.9	69.4 ± 3.1	69.6 ± 3.2	69.9 ± 3.3	70.0 ± 3.5	70.1 ± 3.6	70.2 ± 3.7	70.3 ± 3.8
20	67.9 ± 2.1	68.0 ± 2.2	68.1 ± 2.2	68.3 ± 2.3	68.4 ± 2.4	68.6 ± 2.5	68.8 ± 2.7	69.0 ± 2.8	69.2 ± 3.0	69.5 ± 3.1	69.6 ± 3.3	69.8 ± 3.4	70.0 ± 3.5	70.2 ± 3.7	70.3 ± 3.7
21	67.8 ± 2.0	67.8 ± 2.1	67.9 ± 2.1	68.1 ± 2.2	68.3 ± 2.4	68.4 ± 2.4	68.7 ± 2.6	68.8 ± 2.7	69.0 ± 2.8	69.3 ± 3.0	69.5 ± 3.2	69.7 ± 3.3	70.0 ± 3.5	70.0 ± 3.6	70.1 ± 3.7
22	67.6 ± 2.0	67.7 ± 2.0	67.8 ± 2.1	67.9 ± 2.1	68.1 ± 2.2	68.2 ± 2.3	68.4 ± 2.5	68.7 ± 2.6	68.9 ± 2.8	69.1 ± 2.9	69.4 ± 3.1	69.6 ± 3.3	69.7 ± 3.4	69.9 ± 3.5	70.0 ± 3.6
23	67.5 ± 1.9	67.5 ± 1.9	67.7 ± 2.0	67.7 ± 2.1	67.9 ± 2.1	68.1 ± 2.3	68.3 ± 2.4	68.5 ± 2.6	68.7 ± 2.7	68.9 ± 2.8	69.2 ± 3.0	69.3 ± 3.2	69.6 ± 3.3	69.7 ± 3.4	69.9 ± 3.5
24	67.3 ± 1.8	67.4 ± 1.8	67.5 ± 1.9	67.6 ± 2.0	67.7 ± 2.1	68.0 ± 2.2	68.1 ± 2.3	68.3 ± 2.4	68.5 ± 2.6	68.7 ± 2.8	69.0 ± 2.9	69.2 ± 3.1	69.4 ± 3.2	69.6 ± 3.3	69.8 ± 3.5
25	67.2 ± 1.7	67.2 ± 1.8	67.3 ± 1.8	67.5 ± 1.9	67.6 ± 2.0	67.8 ± 2.1	68.0 ± 2.2	68.1 ± 2.3	68.4 ± 2.6	68.6 ± 2.7	68.8 ± 2.8	69.1 ± 3.0	69.3 ± 3.1	69.5 ± 3.3	69.6 ± 3.4

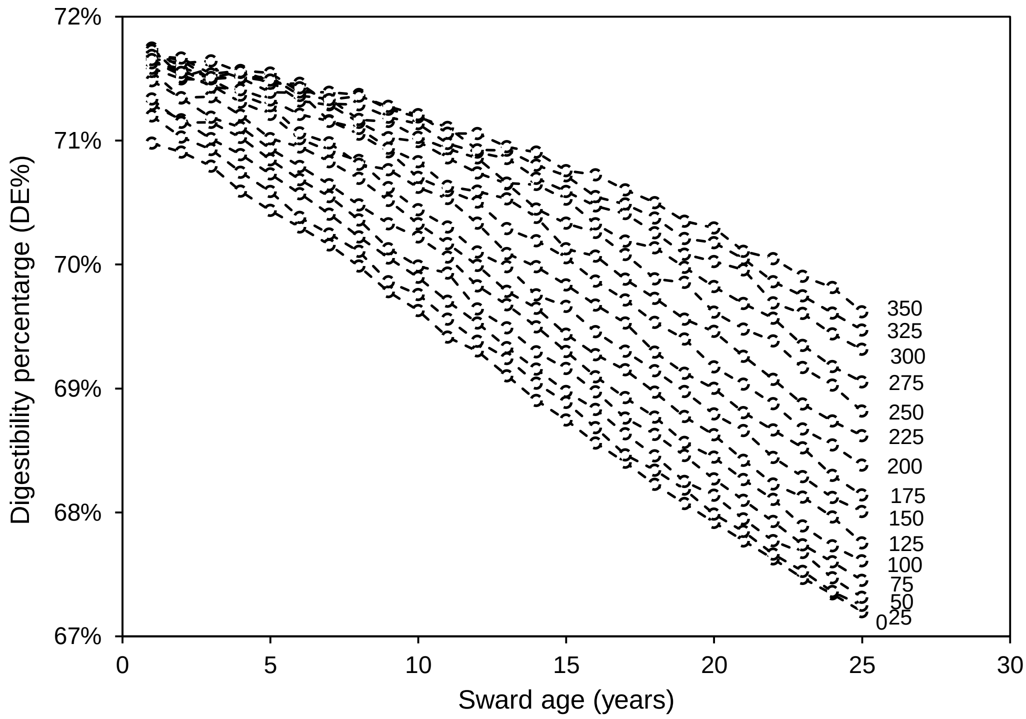

Fig. 5.10. Summary of model Monte Carlo simulation results. Series labels refer to nitrogen application rates in kg N ha^{-1}. A Monte Carlo simulation of 10,000 repeats was run for each year of sward age and N application rate measure.

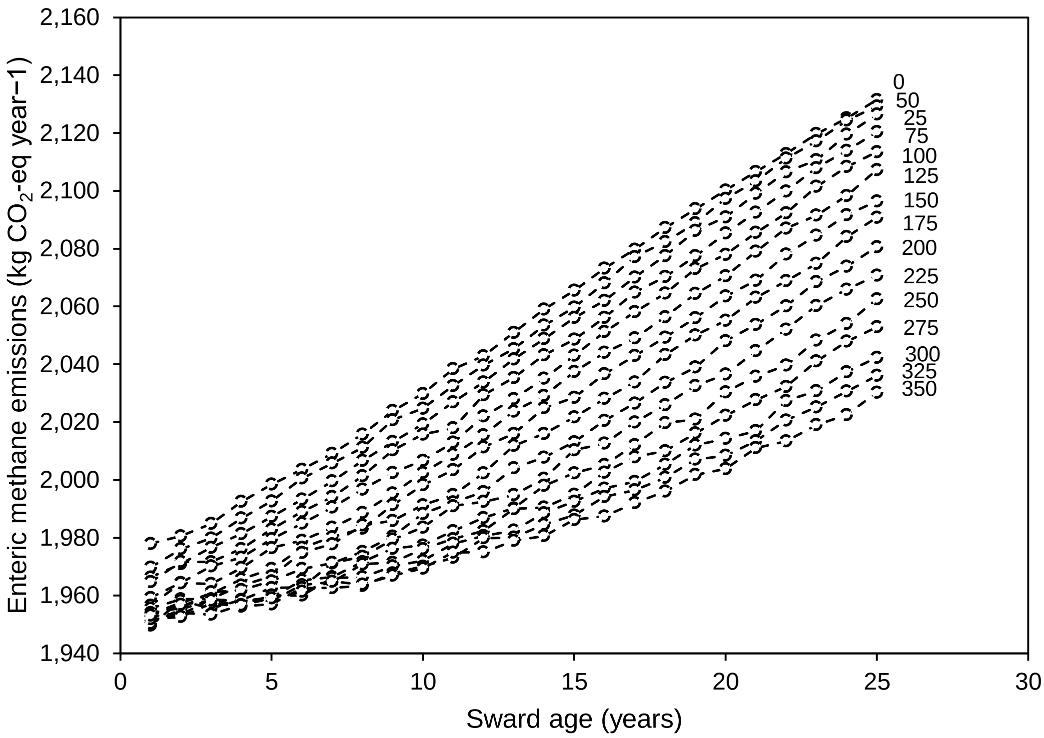

Fig. 5.11. Impact on modelled enteric emissions resulting from Monte Carlo simulation scenarios summarised in table 5.8/Fig. 5.10. Emissions are based on a 670 kg adult female suckler cow with a net energy requirement of 70 MJ day^{-1}. No factors other than feed digestibility were altered. Calculations performed according to IPCC Tier 2 equations as defined by Dong et al. (2006).

Chapter Six

Modelling nutritional characteristics of grazing land for United Kingdom ruminant production systems

Part II: Application and assessment of model in a representative beef production system

6.1. Rationale and background

The introduction to of this thesis demonstrated the importance of efficiency gains in production of beef cattle to global greenhouse gas (GHG) budgets, and the critical role of grazing land as a feed resource in many of these systems; the analyses conducted in chapter four also served to further explore the latter point. As a result of this, calculations of GHG emissions from a ruminant production system are critically dependent on the estimated quality of grazed forage. In order to provide an empirical framework for estimating this variable, chapter five was devoted to the definition of a modelling methodology to estimate the digestible energy percentage (DE%) of grazed grass swards, a key parameter in the IPCC Tier 2 methodology for estimation of enteric emissions from extensive beef production.

IPCC Tier 2 methodology is utilised in numerous life cycle assessment (LCA) studies (e.g. Beauchemin et al., 2011; Cardoso et al., 2016), national-level assessments (Karimi-Zindashty et al., 2012; Milne et al., 2014) and farm-level models (Hillier et al., 2011; see chapter two of this thesis, published as Sykes et al., 2017); as a farm level model, AgRE Calc employs this approach. As identified in chapters three and five, dietary digestibility is typically arbitrarily estimated in these applications of the IPCC methodology. Given the trade-offs inherent in feed production for livestock (Hünerberg et al., 2014), improvement of the way in which this is assessed was identified as a key development area for the AgRE Calc model, which led to the developments described in chapter three of this thesis. These allowed the model to estimate DE% based on the specific ration. Prior to this point, AgRE Calc (SRUC, 2014) characterised dietary DE% and CP% based on expert estimates specific to stated system type (e.g. hill vs. lowland suckler beef).

For the majority of ‘fed’ feedstuffs, nutritional quality remains relatively constant for a given feed type; as a result, the database and calculations described in chapter three was deemed a sufficiently accurate approach for calculation of direct livestock emissions from fed rations in AgRE Calc, and is typically the most complex approach utilised in LCA literature. However, given the documented potential for variability in the nutritional characteristics of grazed grass, and the importance of grazed forage in the diets of beef cattle, it was determined that this approach should be revisited for the parameterisation of grazing land. The development of the model described in chapter five represents the logical conclusion of this process with respect to the grazed roughage component of the ruminant diet. Having defined this modelling framework, the next step of this process was to apply it to a representative production system.

The study described in this chapter therefore has two primary aims:

a) to assess the performance of the modelling framework defined in chapter five of this thesis in the context of a representative beef production system
b) to assess the sensitivity of the modelled emissions intensity of beef production to estimated real-world uncertainty and variability in the quality of grazed forage

To provide a basis for achieving these aims, this study will use AgRE Calc to model a hypothetical United Kingdom beef production system. This will form the basis for a sensitivity analysis to assess the impact of grassland management practices on the modelled DE%, and ultimately on the overall emissions intensity of beef production.

6.2. Development of a modelled beef production system

The system chosen to form the basis of this study was designed as a spring calving, lowland ‘rear-finish’ system producing 18−20 month finished cattle. Whilst suckler beef production systems in the United Kingdom are highly heterogeneous, such a system can nevertheless be deemed relatively typical (SAC, 2016). This system was selected from the array of such ‘typical’ systems because a) because it is a fully integrated system, meaning that production of replacement stock and finishing of production stock takes place on the same enterprise, and b) because it provides the opportunity to finish both heifers and steers; typically, earlier (e.g. 12 month) or more intensive finishing strategies would focus only on male cattle, which provide a better return on investment at this stage. Both of these aspects allow the carbon footprint to focus entirely on one enterprise, rendering both the footprinting process and the subsequent analyses simpler and more transparent. This system was not intended to encompass the full breadth of suckler beef production practices, but rather to provide a representative example with which to explore the study aims and objectives.

The system was designed as a full LCA with a cradle-to-gate scope. In addition to production stock, all replacements and breeding stock, together with their respective feed, bedding and energy requirements, were accounted for. Collated activity data from Data from the 2016 Scottish Cattle and Sheep Enterprise Profitability Report (QMS 2016) provided the basis for estimation of the herd parameters, whilst data from SAC (2016) was employed to estimate cattle live weights for the systems (table 6.1).

Table 6.1. Activity data for the modelled beef suckler system.

Parameter	Units	Value	Source
Bulls per cow	n/a	0.038	QMS (2016)
Calving percentage	%	88.50	QMS (2016)
Calf mortality	%	2.26	QMS (2016)
Cow repl. rate	%	12.00	QMS (2016)
Cow mortality	%	1.70	QMS (2016)
Other cattle mortality	%	0.70	SAC (2016)
Milk production	litres hd^{-1} yr^{-1}	2,200	SAC (2016)
Suckler cow adult live weight	kg	670	SAC (2016)
Bull adult live weight	kg	1250	SAC (2016)

The system was modelled as an annual snapshot, with all necessary replacement breeding animals produced within the modelled system. A common approach is to model an arbitrary herd size, often 100 suckler cows (e.g. Pelletier et al., 2010; Beauchemin et al., 2011), however, this study takes the approach of scaling the herd size to one head of production stock output at the farm gate. This renders the total footprint directly relatable to the production output. Table 6.2 details the numbers and class categories for animals in the modelled system.

Table 6.2. Numbers, weights and performance for animal classes in the modelled system. Numbers are scaled to produce one finishing animal at the farm gate.

	Class	Age (months)	Number (head)	Period duration (days)	Weights (kg)			Daily live weight gain (kg)
					Start	End	Av.	
Breeding stock	Heifer calf (suckling)	0−7	0.1707	212	40	240	140	0.94
	Heifer calf (weaned)	8−12	0.1668	153	240	367	304	0.83
	Replacement heifer	13−24	0.1657	365	367	670	519	0.83
	Suckler cow without calf	Mature	0.1588	365	670	670	670	0.00
	Suckler cow with calf	Mature	1.2218	365	670	670	670	0.00
	Bull calf	0−12	0.0135	365	40	444	242	1.10
	Young bull	13−24	0.0132	365	444	847	645	1.10
	Young bull	25−36	0.0131	365	847	1250	1048	1.10
	Mature bull	Mature	0.0523	365	1250	1250	1250	0.00
Production stock	Finishing calf (suckling)	0−7	1.0376	212	40	260	150	1.04
	Finishing calf (weaned)	8−12	1.0141	153	260	390	325	0.85
	Finisher	13−19	1.0070	212	390	600	495	0.99

Diets for production and replacement animals were defined in the model according to sample data from Morgan and Vickers (2016), HCC Wales (2006) and SAC Consulting (Karen Stewart, pers. comm.). Daily ration quantities were adjusted to reflect class-specific energy requirements, calculated using equations from Dong et al. (2006). Fed rations, in kg hd^{-1} day^{-1}, are presented in table 6.3. Based on system descriptions from SAC (2016), animals were assumed to spend seven months at grass vs. five months housed, with manure in solid storage for the housed period. Dietary digestible energy (DE%) and crude protein content (CP%) were calculated by AgRE Calc (see section 3.1 for methodology) and hence reflected the individual dietary composition. Emissions from the total feed requirements of the beef system were accounted for within the modelled scenario.

Table 6.3. Fed rations (in kg FW hd^{-1} day^{-1}) for the different livestock classes. The system was spring calving, meaning suckling calves and finishing animals from 13−19 months were at pasture and did not require fed rations. All other classes spent 5 months (153 days) housed.

	Age (months)	Straw	Hay	Grass silage	Barley	Rape meal	Distillers' pellets	Maize gluten	Beef concentrate feed	Sugar beet pulp
		kg fresh weight $head^{-1}$ day^{-1}								
Heifer calf (weaned)	8−12	2.22	-	10.14	-	-	-	2.01	1.06	0.84
Replacement heifer	13−24	2.72	-	12.41	-	-	-	2.46	1.29	1.03
Suckler cow w/o calf	Mature	1.60	2.05	4.99	0.19	0.27	0.54	0.59	-	0.43
Suckler cow with calf	Mature	2.11	2.71	6.57	0.26	0.36	0.71	0.78	-	0.57
Bull calf	0−12	1.82	-	8.30	-	-	-	1.64	0.86	0.69
Young bull	13−24	3.43	-	15.70	-	-	-	3.11	1.64	1.31
Young bull	25−36	-	6.53	25.64	-	-	4.66	-	1.28	-
Manure bull	Mature	-	3.85	15.13	-	-	2.75	-	0.76	-
Finishing calf (weaned)	8−12	2.13	-	9.76	-	-	-	1.93	1.02	0.81

For the grazing period, application rate for nitrogen fertiliser and sward regeneration period were defined stochastically (see section 6.3). Application of nitrogen to the modelled pasture area was divided between manure from the livestock enterprise and artificial NPK fertiliser; manure N was given priority up to the maximum produced by the modelled system. The quantity of manure produced by the cattle during the housed period was calculated according to energy calculations from Dong et al. (2006). To mimic a simplistic on-farm calculation, typical values of 25% and 0.012% (Defra, 2010) were employed for manure dry matter content and available N respectively, which resulted in an estimated 5.53 kg of available manure N per year; application rates per hectare were variable as a result of stochastically defined pasture area. Based on recommended practice from SAC (2016), herbicide was modelled as being applied to pasture at a national average rate of 1.08 kg active substance ha^{-1} (Garthwaite et al., 2013).

Allocation of emissions between cull and finishing animals was handled economically, as in PAS2050 (BSI, 2011), using market data from SAC (2016). The functional unit of the simulation was defined as 1 kg of live weight (LW) at the farm gate.

6.3. Development of Monte Carlo simulations

Two Monte Carlo simulations of 10,000 repeats were completed; the first (hereafter referred to as the large-scale scenario) incorporated uncertainties designed to capture the model's applicability at a national or regional level. The second simulation (the farm-scale scenario), controlled for the effects of geographical variability and accounted for uncertainties as applicable at the level of a single enterprise (see chapter five, esp. section 5.3.3 for a description of the derivation of these). For these simulations, the model inputs (nitrogen application rate and sward age) were defined as stochastic integer values. Both were characterised as discrete, integer-step uniform distributions, with nitrogen application rate bounded between 0 and 250 kg ha^{-1}, and sward age bounded to between 1 and 25 years. Nitrogen was applied as organic manure up to the amount produced by the cattle in the housed period, and thereafter in the form of synthetic NPK fertiliser. All of the uncertain parameters in the grassland digestibility model were varied stochastically according to the approach defined in chapter five.

In order to ensure pasture area was accurately modelled, data from SAC (2016) was used to model pasture dry matter (DM) yield response to the defined stochastic variations in nitrogen application. Species composition was assumed not to affect DM yield, an assumption supported by the findings of Rutledge et al. (2017a). Required dry matter intake by livestock was modelled for each class according to equations defined by Dong et al. (2006). This varied according to growth rates and activity (fixed factors), and the digestibility of grazed grass (a stochastically modelled factor). With this information, the estimated required pasture area could be scaled stochastically for each sample in the Monte Carlo simulation.

It is worth noting that there exists considerable variation in many of the input variables defined in tables 6.1 and 6.2, some of which can exert considerable influence over the magnitude of the footprint and emissions intensity. Likewise, there is uncertainty associated with the modelling process itself. Chapter four of this thesis accounted for aspects of this variability, and chapter seven is focused around an assessment of epistemic uncertainty in farm-level GHG models. For the purpose of this study, however, it was determined that these values should remain deterministic, in order to provide maximum analytic potential for the grassland parameters under assessment.

6.4. Results

6.4.1. Performance of sown species density regression models

Visual appraisal of the Monte Carlo simulation results suggested that the trends present in the raw data (see section 5.3) were effectively approximated by the chosen parameters and distributions (Fig. 6.1). Though trends were consistent between the scenarios, as expected, the large scale scenario demonstrated much higher variability in the response variable. Sward age proved to be a stronger predictor variable than nitrogen application rate, with a more consistent response for both scenarios; this was in part due to its greater strength as a predictor in the regression models for both sown grasses and clover, but it is likely that the differing direction response for nitrogen application rate of *T. repens*, as compared to sown grass spp., acted to increase the variability of this response for sown spp. as a group. Fig. 6.1 shows an overall positive response to nitrogen application for sown spp. density, indicating that this response is dominated by the greater proportion of sown grasses to *T. repens*, which showed a negative response.

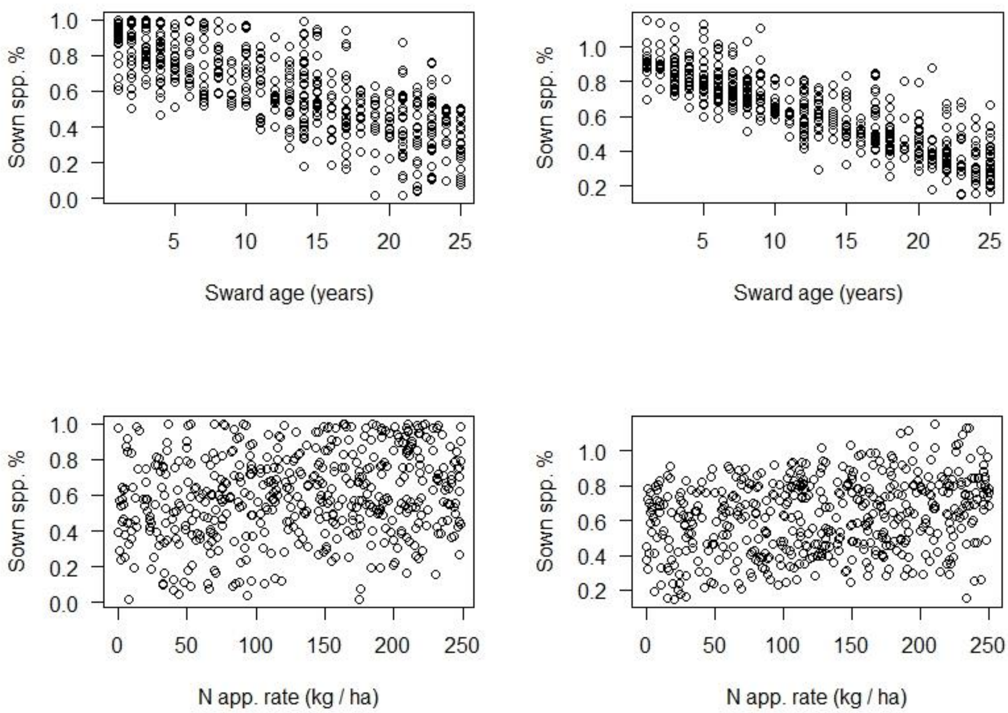

Fig. 6.1. Performance of the regression models for sown spp. density in the Monte Carlo simulation. Data shown is from the large-scale scenario (left) and farm-scale scenario (right). (*N.B.* to maintain visual clarity, only the first 500 of 10,000 simulations are plotted).

6.4.2. Response of pasture digestibility to model inputs

Pasture DE% showed a strong, positive response to the modelled proportion of sown spp. in the sward (Fig. 6.2), indicating that the proportion of sown spp. as predicted by the regression models had a strong effect on this variable. For the farm-level simulation, where uncertainties in intra-specific digestible energy percentage resulting from differences in sampling environment were controlled for, the spread of the response was much tighter, indicating this remains an important factor in the uncertainty of the model as a whole.

The slope of the response variable was 0.076, indicating that a 1% increase in sown spp. in the sward would result in a 0.076% increase in sward digestibility; or that a change from 100% to 0% sown spp. in the sward would reduce the digestibility by 7.6%.

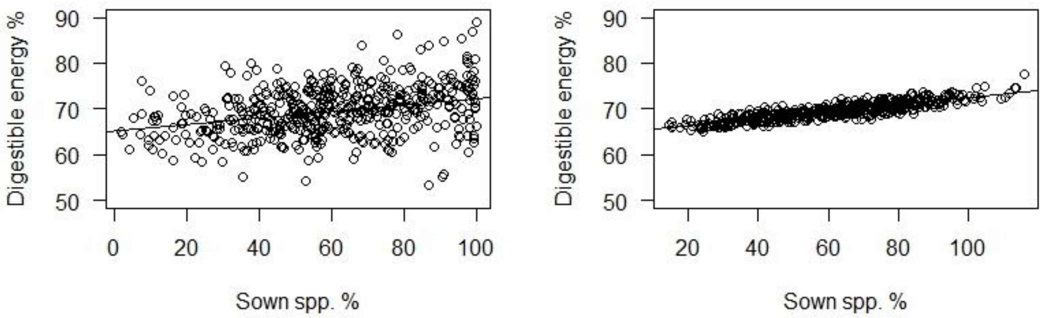

Fig. 6.2. Response of the pasture digestibility to the proportion of sown spp. in the sward. Data is from large-scale scenario (left) and farm-scale scenario (right).

Having examined the direct relationship between sown spp. density and pasture digestibility, it is of interest to assess the impact of the regression model inputs. This is effectively combination of two sets of uncertainty in the model; firstly uncertainty in regression predictive power, and secondly uncertainty in intra- and inter-specific digestibility. As expected, results are most tightly grouped for the farm-level scenario, where these both sets of uncertainty were lower in magnitude. It is worth noting that the slope of the regression lines are the same for both simulations scales, meaning the average scale of the response is constant.

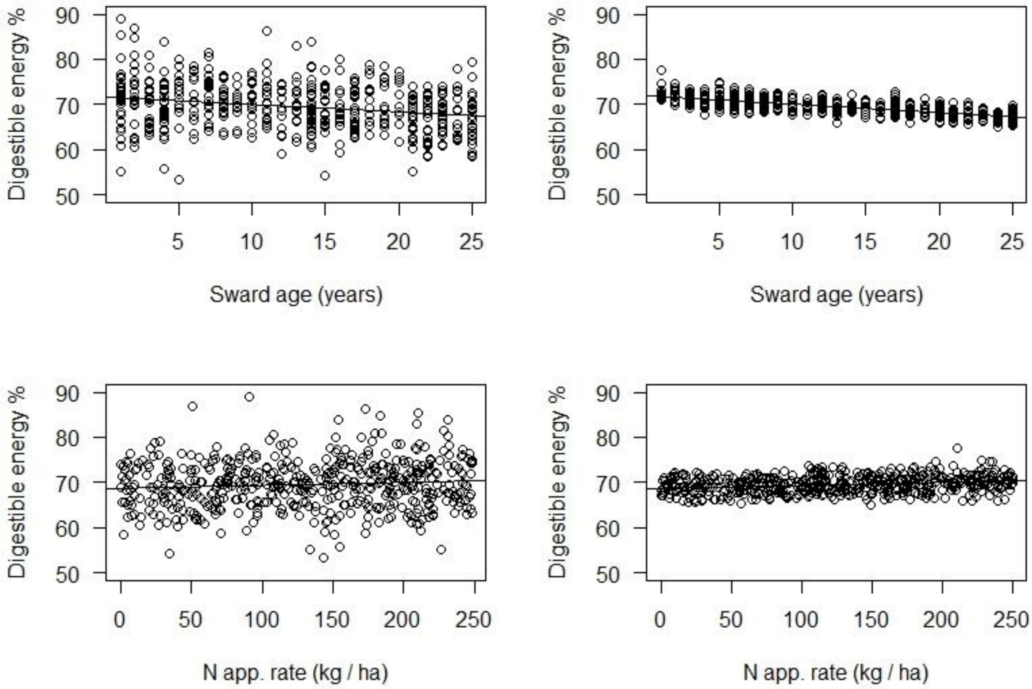

Fig. 6.3. Performance of the model for prediction of pasture digestible energy % in the Monte Carlo simulation. Data shown is from the farm-scale scenario (right) and large-scale scenario (left).

For nitrogen application rate (Fig. 6.3), the slope described by the response variable was 0.007, indicating that for an additional 1 kg ha^{-1} increase in application rate of nitrogen fertiliser, the pasture digestibility would increase by 0.007%. Given the range of the uncertainty, and the range of spp. specific DE% values present in the sward, this is a relatively weak response. It is likely to reflect both the lower impact of nitrogen application rate on sown spp. density, and difference in response directions demonstrated by *T. repens* as opposed to the sown grass sward.

Sward digestibility demonstrated a stronger response to the age of the sward, with an increase in sward age of one year equivalent to a decrease in DE% of 0.19%. Both sown grasses and *T. repens* demonstrated a consistent (negative) response to sward age, and overall the effect size and explanatory power of the variable was larger in both models.

6.4.3. Effect of pasture digestibility on the emissions intensity of production

With variable sward regeneration periods and nitrogen application rates contributing separately to variability in the carbon footprint (affecting crop residue emissions and fertiliser production/application emissions respectively), digestibility of the grass sward as it varied within the modelled scenarios can be seen to be instrumental in impacting the emissions intensity of beef production (Fig. 6.4).

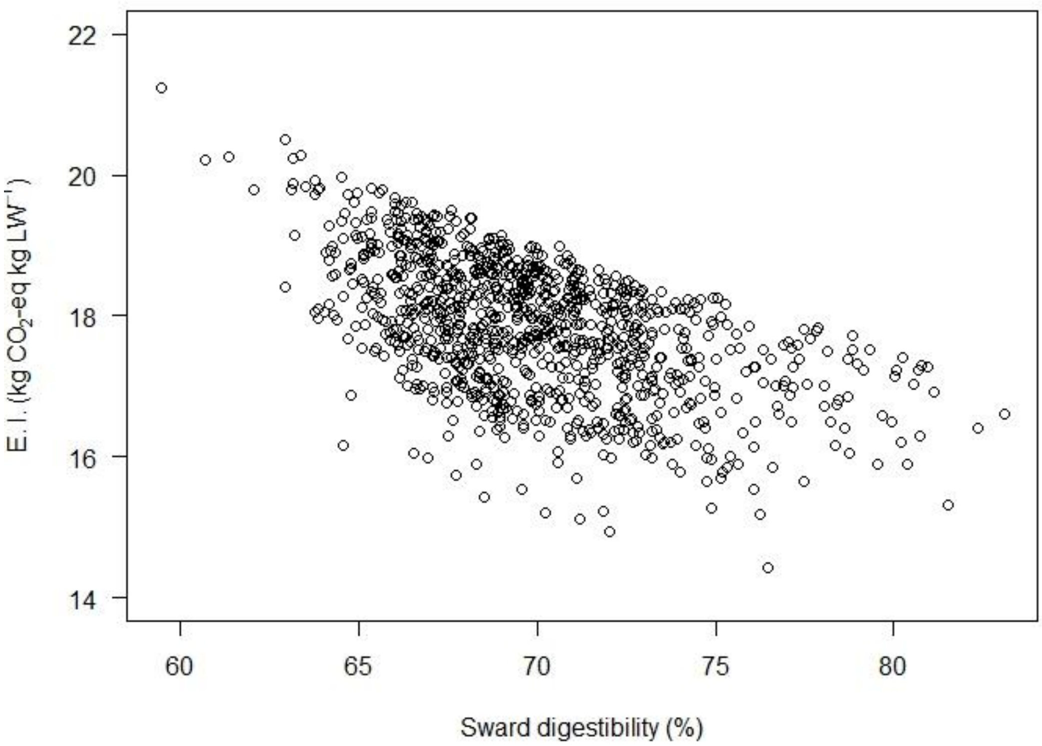

Fig. 6.4. Effect of the digestible energy percentage of grazed pasture on the overall emissions intensity of beef production for the modelled system. Unexplained variability results from variation in crop residue and fertiliser emissions. Data is from the large-scale scenario, but given the variables involved, response is similar for the farm-scale scenario.

The response of enteric methane to digestibility of the diet is curvilinear in the model (proportional to 1 / DE%^{2}), an effect which can be seen in Fig. 6.4. As a result, lower digestibility values result in exponentially higher enteric methane response, making it an important factor to consider in terms of mitigation.

6.4.4. Effect of model inputs on emissions intensity of beef production

Simulation of a beef production system linked to the sward digestibility model enabled assessment of the effect of the base inputs (nitrogen application rate and sward age) on the emissions intensity of production. The beef production system produced an estimated final emissions intensity of 17.81 ± 0.93 kg CO_2-eq kg LW^{-1} for the large-scale scenario, and 17.83 ± 0.77 kg CO_2-eq kg LW^{-1} for the farm-scale scenario. As described in section 6.2, the beef herd and feed parameters were fixed, so the variation in the emissions intensity resulted from a combination of the sensitivity of the emissions intensity to the stochastically defined model inputs (sward age and nitrogen application rate) and to the uncertainties in the sward digestibility modelling process.

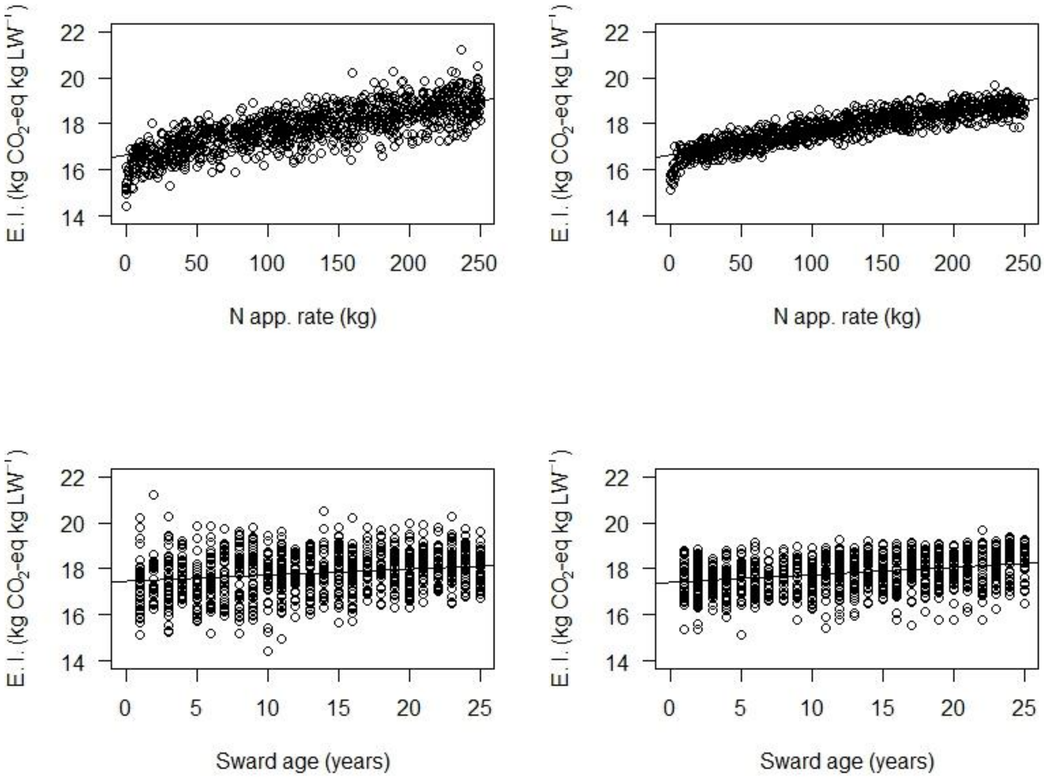

Fig. 6.5. Sensitivity of the emissions intensity of beef production to variation in the stochastically defined sward model inputs. Data is plotted for the large-scale scenario (left) and the farm-scale scenario (right).

Nitrogen application rate was found to be positively correlated with the emissions intensity of production for the modelled beef system (Fig. 6.5). Whilst it can be seen that nitrogen application rate acts to increase the digestibility of the sward (Fig. 6.3), which in turn reduces the system's enteric emissions, it is clear that the additional emissions from the application and production of nitrogen fertiliser act to outweigh this saving.

A linear model describes this relationship reasonably well (Fig. 6.5), though several non-linear interactions in the model mean that it is not a true fit. In particular, it is worth noting that the gradient of emissions intensity increase appears to reduce at rates of roughly 5 - 10 kg ha^{-1}. This is caused by the nature of the modelled system; nitrogen application rate was defined arbitrarily and stochastically (from 0 – 250 kg ha^{-1}), with priority given to available N from manure produced by the herd during the housed period; this equated to 8.22 ± 0.96 kg ha^{-1}. Where the defined N application rate was lower than this, manure was assumed to be applied to other crops or grassland to adjust for this imbalance, while when the defined application rate was higher, synthetic nitrogen fertiliser was imported and applied to the pasture. The sharp increase results from emissions relating to manure production and application (CH_4 and N_2O) being allocated out of the modelled system up to the application rate of around 8.22 kg ha^{-1}.

Sward age showed a positive correlation with production emissions intensity, indicating that beef systems grazing older swards showed higher overall emissions intensity. A fitted regression line showed that this relationship could be approximated to a linear interaction, which explained 2.2% of variability in the modelled farm-scale scenario ($F = 222.2$, $p < .0001$), and 1.0% of the variability in the large-scale scenario ($F = 97.1$, $p < .0001$). The vast majority of remaining variation could be explained by input variation in pasture fertilisation and stocking rate. The slope described by the response indicated that that the emissions intensity increased by 18.27 ± 1.22 g CO_2-eq kg LW^{-1} for every year of increased sward age.

6.4.5. Sensitivity of EI to pasture digestibility

This section examines the impact of variation in pasture digestibility on the overall emissions intensity of the production system. The aim is to quantify numerically the impact of variation (both explained and unexplained) on the emissions intensity with a view to providing a basis for discussion of the impact of this factor on uncertainty of calculations of beef emissions intensity.

In the case of the current beef system, the 95% confidence interval for pasture digestibility percentage ranged from 65.9 – 73.2 (farm-scale scenario) and 59.4 – 79.7 (large-scale scenario). These values were calculated across the ranges of the stochastically defined input variables. Higher uncertainty in both intra-specific digestibility values, and sown spp. density response to sward age and nitrogen application were the causes of the differing ranges. As discussed in section 3.1, the modelled enteric methane response to digestibility is inverse and non-linear (Dong et al., 2006). For the defined beef system, the following linear model was fitted to the results data to describe the enteric methane response in relation to the DE% ($F = 9.82 \times 10^7$, $R^2 = 1$):

Equation 6.1. Relationship between enteric methane and digestible energy percentage of ration.

$$CH_{4\,enteric} = A\left({}^{1}/_{DE^2}\right) + B$$

Where:
A = 7.869 × 10^{-3} ± 1.648 × 10^{-4} (kg CO_2-eq kg LW^{-1})
B = 9.707 ± 7.941 × 10^{-1} (kg CO_2-eq kg LW^{-1})
$CH_{4\,enteric}$ = methane from enteric fermentation, in kg CO_2-eq
${}^{1}/_{DE^2}$ = scaling factor derived from digestible energy of pasture, as a % of gross energy (*dimensionless*)

Using eq. 6.1, the variation in the contribution of enteric emissions to total emissions intensity of production based on modelled variation in pasture digestibility could be estimated. The results of this are summarised in table 6.4.

Table 6.4. Variability of enteric emissions intensity (in kg CO_2-eq kg LW^{-1}) based on sensitivity to variation in modelled pasture digestibility. Variation results solely from the impact of diet digestibility on emissions from enteric fermentation.

	Min	*5% CI*	*M*	*95% CI*	*Max*
Farm-scale	11.02	11.20	11.34	11.48	11.64
Large-scale	10.69	10.94	11.36	11.78	13.35

Table 6.4 shows that, within an individual farm, the modelled variability in pasture digestibility has a measurable impact on the overall emissions intensity of production. In the case of the large-scale scenario, the additional variability in DE%, resulting from additional uncatalogued variation in management and climate-related factors, causes increased uncertainty in the emissions intensity.

6.5. Discussion

6.5.1. Assessment of approach

This study successfully quantified the impact of a number of factors that affect the digestibility of grazed grass swards. This represents an improvement in flexibility and objectivity over the expert estimate approach typically used to date in farm-level modelling (e.g. Hillier et al., 2011), national GHG inventory reporting (e.g. Brown et al., 2016) and LCA literature (e.g. Dick & da Silva, 2014; Cardoso et al., 2016). This study also highlights the importance of properly quantifying digestibility of grazing land for modelling approaches.

Additionally, the modelled results demonstrate the large variability and uncertainty surrounding the parameterisation of this variable, which provides both a) cause for caution, given the impact this can have on the emissions intensity of ruminant livestock production, and b) a viable area for further investigation, given the demonstrated potential for reduction in enteric emissions based on increased digestibility of pasture.

The model development was constrained by limited input data availability; a deliberate approach given its intended direct application (see section 5.2.1). However, there is scope for further improving the model's ability to account for the impact of further grassland management approaches without necessarily invalidating its aim of maintaining accessibility through low data input burden (section 6.5.3).

6.5.2. Explanatory power of model

The process of model development showed that nitrogen application rate and sward age were both statistically significant predictors of sward composition. In relation to high levels of modelled uncertainty in sward composition, however, the model showed relatively low explanatory power when comparing primary inputs (sward age and nitrogen application rates) to final outputs (emissions intensity of beef production) for the large-scale scenario. This to some extent reflects the multiple-step nature of the model which, though necessary to capture a complex set of interactions, allows for the propagation of uncertainty with each step. In turn, this reflects the difficulties associated with simplifying complex scenarios to fit modelling requirements, particularly where input data is limited. This is representative of the challenges of farm-level modelling as a whole.

Explanatory power was improved for the small-scale scenario, indicating that where this model is applied on a local scale (and in particular where it is used to compare hypothetical or before-and-after scenarios), the management factors accounted for in this approach are sufficient to provide an estimate of the resulting impact on digestibility and emissions intensity of production.

The benefits of application of synthetic nitrogen in the reduction of enteric emissions were outweighed by the costs of N_2O emissions from land, and of emissions incurred in the production of synthetic nitrogen fertiliser. Where organic nitrogen is applied, this effect is less defined, given that no production emissions are incurred.

However, reduction in enteric emissions resulting from shorter sward regeneration times outweighed the resulting increase in annual crop residue emission share. This study provided an estimate of the emissions abatement potential of 23.06 ± 1.55 g CO_2-eq kg LW^{-1} for each year by which sward age is reduced. Given the magnitude of the average emissions intensity of production (25.0 kg CO_2-eq kg LW^{-1}), this does not represent a large percentage of the overall footprint. However, analysis of the collated data from Forbes et al. (1980) and Swift et al. (1983) (see section 5.3.2) shows that the average sward age for improved grazing land in the sample was 13.1 years (N = 206). In 2015, Scotland produced 307,400 tonnes (LW)[14] of finished beef cattle for meat (SGDEF/RESAS, 2016). A broad calculation based on the results of this study suggests that if the average age of grassland used for beef cattle production was halved, it could result in the abatement of over 46.4 kt CO_2-eq of enteric methane annually (though note

[14] Converted from carcass weight (CW) using a conversion factor of 1/0.55 (Opio et al., 2013).

that this ignores the emissions associated with pasture renovation, which may be significant; see section 6.5.4).

It should be noted that the above calculation represents a very broad extrapolation of the results of this study, and should be regarded as an indicator of the magnitude of the abatement potential rather than as a specific recommendation based on the modelling outcome. It is nonetheless useful to provide an initial quantification of this potential, rendering it open for discussion and further consideration.

Additionally, pasture regeneration may have adverse effects on grassland biodiversity, both directly, in terms of grass species, and indirectly, in terms of other species reliant on diverse grasslands (JHI, 2016). This is an important factor to consider if advocating an increase in the frequency of pasture renovation for the purposes of reducing GHG emissions.

6.5.3. Opportunity for further model development

The cutting regime employed on grassland has been shown to have a significant quantifiable effect on both the species assemblages and the intra-specific nutritional quality of a grazed sward (Ergon et al., 2016). Brief review of the literature suggests that the effects of this practice may be quantifiable using existing data, and could serve to reduce the uncertainty present in the current model in terms of sward spp. composition and digestibility. AgRE Calc does not currently collect input data on cutting regimes, as this management practice does not directly impact modelled GHG emissions in the current version. However, details of cutting regimes are likely to be well known to land managers, and as such the increase in data input burden would not serve to impact the model's applicability.

In addition, Hopkins et al. (1988) quantified the effects of altitude on species assemblages in grassland, showing that sown ryegrass species typically fare better at lower altitudes, whilst some native species such as *Festuca rubra* are more able to compete at higher elevations. These native species are typically much less digestible and hence high elevation swards are likely to degrade faster in terms of nutritional quality (given the low durability of species such as *L. perenne* at high altitudes, they are also less likely to be cultivated in the first place). It would likely be possible to derive estimates of altitude from the original datasets of Forbes et al. (1980) and Swift et al. (1983) which could serve to bolster this finding. The altitude of a holding may well be known to a typical farmer, but if not, other locational identifiers (e.g. postal/ZIP code) could feasibly be used to identify this and would not represent a significant increase in data input burden. The main limiting factor here is the availability of a dataset which integrates altitude alongside other factors; whilst Hopkins et al. (1988) summarised these data, there was no way of integrating the published datasets. Temperature, rainfall and soil type also impact the development of the sward and the species assemblages which form (Frame, 1992). These would be interesting variables to include in the model, and again, base data would likely be derivable from the original datasets of Forbes et al. (1980) and Swift et al. (1983). Factors such as average annual temperature and rainfall, as well as soil type, would be retrievable based on location to a reasonable degree of accuracy from GIS databases. However, topographical factors, such as incline, influence soil drainage and may be harder to characterise, given the small scale upon which variation occurs. Requiring this data to be manually input could represent an unacceptable increase in data input burden.

An additional point, worth noting in relation to the inclusion of environmental variables in the modelling process, is that farm-level models are increasingly being considered as auditing tools with a view to reducing agricultural emissions via policy. Where tools are used to derive policy aimed at promoting low emitting enterprises, care would have to be taken to ensure that estimates incorporating a factor such as altitude or temperature, which is a locational feature rather than a voluntary management practice, do not result in adverse policy impacts on enterprises which have high predicted emissions as a result.

Aside from adding variables to better define species assemblages, it may also be possible to refine the estimates used for digestible energy percentage of individual species. Intra-specific digestibility was defined in the model based on a relatively small sample size (see table A.6). Consequently, there is a relatively high uncertainty in some estimates. Whilst this uncertainty is represented in the model, it is possible that it could be reduced through an increase in sample size. While the utilised sample represented a thorough search of the published literature, it is likely that more estimates exist in grey and unpublished literature.

In addition to simply increasing sample size, the inclusion of certain management variables (such as cutting regime) which are known to have an effect on intra-specific digestibility (Frame, 1992) would also improve estimates as utilised in the model. These could be incorporated as management parameters into the temporal baseline approach to ‘translate’ species-specific estimates of digestible energy percentage. It is also noted (Frame, 1992) that different species follow different patterns and timescales of development over the course of the summer grazing season, and so whilst the temporal baseline approach used in the model (section 5.3.1) adequately captures the general trend, it is likely that the adoption of a species-specific temporal baseline would reduce the uncertainty in this variable. To make this possible would require a much larger sample dataset, relating DE% to season and species.

6.5.4. Soil carbon sequestration in grazed land

In considering the impacts of management strategies on GHG emission from pasture-based livestock systems, it is important to consider the potential impact of soil carbon sequestration by grassland. A number of management practices can influence soil C stocks, but the effects of these are difficult to quantify at farm level, and hence were not directly included in the model. Nonetheless, the accumulation or release of CO_2 can form a substantial component of the carbon footprint of ruminant production (Subak, 1999; de Oliveira Silva et al., 2016).

Where grass swards are renewed, loss of CO_2 uptake from photosynthesis, combined with microbial degradation, may act to reduce soil C uptake. However, grassland sward biodiversity has been identified as having potential to positively influence accumulation of soil carbon (Rutledge et al., 2017a). The authors found that where pastures were renewed via direct drilling, sowing a more diverse sward aided C retention by soil, though did not find compelling evidence that this increased soil C retention compared to an unmodified ryegrass sward. Rutledge et al. (2017b) found that whilst pasture renewal negatively impacted soil carbon uptake, it did not result in net carbon emissions from soil. More important than the method of renewal was the fallow time, which represented a period with decreased CO_2 uptake and increased microbial losses. It is worth noting that these conclusions (Rutledge et al., 2017a, 2017b) were drawn from grazed swards, and it was also found that application of carbon stock to the newly renovated pasture, in the form of manure, effluent or supplementary feed for livestock may act to reduce net carbon loss from the renewal process.

It is therefore important to realise that if recommending an increase in frequency of pasture renewals to reduce enteric emissions from grazing ruminants, soil carbon losses may increase and counteract this saving. However, it may be possible to offset these losses by increasing pasture biodiversity, so sowing a more even mix of desirable species, such as *D. glomerata* and *P. pratense* in addition to the typical *L. perenne* and *T. repens* mix, could represent a win-win in terms of mitigation of enteric emissions, together with neutral or positive soil carbon response. In addition, if adding nitrogen to newly renovated swards, manure or effluent may represent a better choice than inorganic N, given that a) it has no emissions associated with production and b) the renovated pasture may benefit from addition of the carbon present in organic fertilisers.

6.6. Conclusions

This study represents first and foremost a demonstration of the complexities involved with characterisation of the nutritional characteristics of grazing land in livestock carbon footprinting. Building on this, the modelling approaches defined herein provide an initial empirical approach towards parameterising these variables for temperate European productions systems, whilst the broader methodology also provides a blueprint by which such assessment may be made for other world regions. Many studies and models rely on the IPCC Tier 2 approach (Dong et al., 2006) to model GHG emissions from livestock production, but typically rely on arbitrary and often unsubstantiated estimates of pasture digestibility. This study demonstrates the sensitivity of the overall footprint pasture DE%, and quantifies the potential for variability in this parameter demonstrated by grazing land. In explaining a proportion of this variability, a tool is provided which will assist in the accuracy and flexibility of LCA estimates, and help quantify trade-offs associated with improving pasture quality for the mitigation of enteric emissions.

In quantifying the uncertainty surrounding predictions of pasture DE%, this study provides a basis for sensitivity analysis of LCA estimates to this factor, and gives a framework for the refinement of the ‘first-steps’ modelling approach defined herein. Opportunities have been identified for the assessment and inclusion of additional explanatory variables in different stages of the model which have potential to increase the explanatory power and regional specificity of the estimate, without increasing the data input burden beyond the defined limits. Further development of this modelling approach would not only reduce the uncertainty surrounding estimates, but would provide opportunity for the assessment of further mitigation strategies and associated trade-offs.

Chapter Seven

Mapping uncertainty in the greenhouse gas footprint of beef production

7.1. Introduction

As biological systems, beef production systems are fundamentally complex, and limitations in the methodological ability of life cycle assessment (LCA) studies to accurately capture the intricacies of this represent a major challenge both to practitioners and users of the approach (Röös & Nylinder, 2013). Accordingly, results obtained from LCAs of beef systems carry considerable uncertainty, and this can impact their interpretation in a decision-making context (Gibbons et al., 2006); this is largely due to errors and omissions in input data, and limitations in the conceptualisation of the model framework (Milne et al., 2015). This uncertainty, particularly where emissions arise from a number of different sources within a modelled system, is therefore important to quantify (Röös & Nylinder, 2013). In accordance with this observation, a stated aim of this thesis (section 1.4.4) was to explore the potential for characterisation of uncertainty in results produced using the AgRE Calc model. To permit this assessment to be made, a considerable amount of development was undertaken (section 3.4) to the model to enable Monte Carlo simulation to be employed as a tool to conduct uncertainty and sensitivity analyses.

Farm-level LCAs and GHG accounting tools frequently rely on methods and guidance published by IPCC (e.g. Hillier et al., 2011; Dudley et al., 2014; Cardoso et al., 2016). The 2006 Guidelines (IPCC, 2006), designed for national-level GHG reporting, are a common choice in this respect. In recognition of the uncertainties associated with a modelled approach such as this, countries reporting within the IPCC framework are required to quantify the impact of uncertainty on national level estimates of GHG emissions. Chapter two of this thesis (published as Sykes et al., 2017) demonstrated that utilisation of this methodology at farm level requires a degree of interpretation and adaptation. However, considerations of uncertainty are not commonly accounted for in farm-level assessments. The way in which uncertainty applies is also different on smaller scales; input data is likely to be more certain for a specific farm-scale assessment, though being site- and situation-specific, uncertainty in the generalised coefficients and emission factors presented by a national-level methodology may be greater.

Some previous approaches have made use of Monte Carlo simulation to assess uncertainty in production of beef (Gibbons et al., 2006; Dudley et al., 2014) and dairy products (Lovett et al., 2008; Zehetmeier et al., 2014). Focus, however, has typically been on the final result, meaning limited interrogation of the data to determine the root causes of uncertainty is possible. However, these assays serve to highlight a) the wide uncertainty in the GHG intensity of beef production and b) the range of sources which contribute to uncertainty in the footprint. Delving further into this, Milne et al. (2014) conducted a Monte Carlo-based uncertainty and sensitivity analysis of N_2O and CH_4 emissions modelled for the United Kingdom national GHG inventory. Based on the results of the sensitivity analysis, the authors were able to gain insight on the impact of individual coefficients on the final modelled results.

Breaking down the approach, Röös & Nylinder (2013) identify several areas which may contribute to uncertainty in the carbon footprint of a livestock system; namely,

a) uncertainty or variability in input data,
b) uncertainty resulting from scenario choices such as scope and allocation method, and
c) uncertainty in modelling approach used to assess emissions from biological systems

Considering this range of sources, it is arguable that focusing on a specific category of uncertainty may yield greater transparency in results and enable more specific conclusions to be drawn. As previously identified, uncertainty in input data (a) is likely to be considerably lower for a farm-level assessment than for a dataset which is intended to be nationally representative. Decisions relating to scope and allocation method (b) are important at farm-level, but a degree of consensus is emerging in this respect and for the majority of published studies, this consideration is usually relatively transparent. The effects of inclusion/omission of emissions sinks and sources are also relatively well documented (e.g. Flysjö et al., 2012), as are the impacts of different allocation methods (Nguyen et al., 2012). However, the modelling approach used to capture and quantify emissions from different sources (c) remains a considerable challenge and source of uncertainty in both farm- and national-level LCA assessments (Röös & Nylinder, 2013). This is further exacerbated by the complexity of livestock systems, both biologically and in terms of interactivity between system components. Milne et al. (2014) provided considerable insight into this at national level; however, the necessarily broad scope of a national-level assay means that results are not focused on a particular livestock product. Given the demonstrable role of holistic farm-level LCAs in understanding and mitigating greenhouse gas (GHG) emissions from beef systems globally, and the extent to which these approaches differ from national-level assessments, the requirement is clear for a comprehensive analysis of the causes and impacts of uncertainty in farm-level modelling of beef production systems.

National-level assessments of agricultural emissions (e.g. Milne et al., 2014) also differ from holistic farm-level LCAs in the range of emissions sources they consider; indirect emissions from production in other sectors (e.g. agrochemicals) are not considered as agricultural emissions national-level assessments, but are typically important in estimates of GHG emissions made in a farm-level LCA. Given the impacts of uncertainty in terms of interpretation of LCA output, and the importance of beef production to GHG budgets both national (Committee on Climate Change, 2010) and global (Caro et al., 2016), this study identifies the causes and impacts of uncertainty in the modelling process for a holistic farm-level GHG footprint of United Kingdom beef production. Propagation of uncertainty in a complex modelled system can be convoluted and counter-intuitive; recognising this, this study employs Monte Carlo simulation to trace uncertainty propagation throughout a the GHG footprint of a beef system modelled at farm-level. The most sensitive parameters are identified, providing the basis for a discussion of a) improvement of farm-level GHG footprint modelling, and b) interpretation of model output by LCA practitioners, users and decision makers.

7.2. Methods

7.2.1. Modelled beef suckler system

The system chosen to form the basis of this study was designed as a spring calving, lowland 'rear-finish' system producing 18−20 month finished cattle. The modelled system, with minor modifications (described below) was identical to that defined for the analyses described in chapter six of this thesis (see section 6.2 for system description). The rationale for the system choice is similar in that the scenario represents a fully integrated production system representative of United Kingdom production practices. As in section 6.2, the system was defined as a full LCA with a cradle-to-gate scope; all production stock and all replacements and breeding stock, together with their respective feed, bedding and energy requirements, were accounted for.

In section 6.2, certain input parameters (namely fertiliser application rate and grass sward regeneration period) were defined stochastically for the purposes of the analyses conducted in chapter six of this thesis. Since this study focuses primarily on uncertainty in the modelling process, these input parameters were defined deterministically in this assessment to avoid generating extraneous uncertainty in results. Differing from the section 6.2 scenario, the modelled pasture area received 150 kg N ha^{-1} and was assigned a 7-year renovation period; whilst rates of fertiliser application and pasture renovation vary, these represent typical median values for lowland pasture in the United Kingdom (SAC, 2016). Based on this application rate and data from SAC (2016), pasture was estimated to produce 8,740 kg DM ha^{-1}. Digestible energy from grassland was calculated using a constrained run of the model developed in chapters five and six of this thesis (see table 5.8 for this model output), and this value, together with calculated energy requirements for the grazing period (based on Dong et al., 2006), were used deterministically to define pasture DM requirements and allocation between classes; 0.65 ha was required in total to support production and breeding stock. As a spring calving system, calves were suckled entirely at pasture; calculated energy provision from lactating cows was used to scale additional grazing requirements for suckling calves.

As in section 6.2, typical values of 25% and 0.012% (Defra, 2010) were employed for manure dry matter content and available N respectively, which resulted in an estimated

5.53 kg of available manure N per year. For a fixed pasture area of 0.65 ha, this equated to an application rate of 8.55 kg N ha^{-1} to the grazing land. The remaining nitrogen requirements of the land (141.45 kg ha^{-1}) were supplied by the application of 91.59 kg of artificial NPK fertiliser, also supplying the phosphorous and potassium requirements of the grassland. Herbicide was modelled as being applied to pasture at a national average rate of 1.08 kg active substance ha^{-1} (Garthwaite et al., 2013).

As in section 6.2, allocation of emissions between cull and finishing animals was handled economically, as in PAS2050 (BSI, 2011), using market data from SAC (2016). The functional unit was defined as 1 kg of live weight (LW) at the farm gate.

7.2.2. Modelling approach and uncertainty analyses

This assessment was defined as a farm-level holistic LCA. The scope of the assessment was defined around this, and the following on-farm GHG sources were modelled: N_2O emissions from crop residues, fertiliser application and manure application and deposition; CH_4 from enteric fermentation and manure; CO_2 from diesel use. In addition, off-farm (embedded) GHG emissions were modelled from production of livestock feed, bedding, fertiliser, pesticide and electricity used as part of the modelled production system. The functional unit of the analysis was defined as one kg beef live weight (LW) at the farm gate.

The farm-level footprinting model AgRE Calc (SRUC, 2014) was used to provide a footprint estimate for the modelled beef system. Full details of model functionality are given in Sykes et al. (2017) (included as chapter two of this thesis); details specific to this study are related to characterisation of uncertainty in the modelled system, and are summarised here. It is first necessary, however, to make distinction between the sources of uncertainty in the model.

Uncertainty can stem from variability (e.g. temporal, spatial) in natural and managed systems; this may to some extent be mitigatable through management practices, but (once scope is defined) cannot be reduced by the modelling approach. The remaining uncertainty can be classified as epistemic (Groen et al., 2017), and is fundamentally derived from lack of understanding of, or ability to capture the intricacies of complex biological systems

This study is designed to assess epistemic uncertainty relating to the beef production system as modelled at farm level. In this sense, a great deal of uncertainty derived from natural variability is represented as epistemic uncertainty, given that the emission factors used to calculate the footprint do not account for spatially or temporally variable factors (such as climate). As such, uncertainties in modelling coefficients are designed to encompass geographical and temporal variation in emissions.

Aside from natural variability, and depending on the scope of the assessment, variation in production practices means that input data for any modelled real-world production system is likely to exhibit some uncertainty. This may be of considerable importance in the overall model (e.g. Dudley et al., 2014), but its nature and magnitude is likely to be relatively situation-specific, and hence non-generalisable. Accordingly, input data for the modelled system (as defined in section 7.2.1) is treated as certain; in doing this, the remaining uncertainty, which represents the epistemic uncertainty in a holistic LCA model of a suckler beef production system, is isolated. Thus defined, this category of uncertainty forms the basis of this assessment. The following sections describe the characterisation of this modelling uncertainty within AgRE Calc.

ModelRisk (Vose Software) was incorporated into the AgRE Calc model to provide Monte Carlo functionality. Utilising the input data described in section 7.2.1, the model was calculated for one annual timestep. The model was run both deterministically, using best estimate values for the coefficients, and a Monte Carlo simulation of 10,000 repeats (Mersenne seed = 2605) was conducted, which formed the basis for the uncertainty assessment.

7.2.2.1. Methane from livestock and manure

Data from Dong et al. (2006) was used to quantify uncertainty in methane emissions from livestock. This data typically took the form of best, minimum and maximum estimates. Where these distributions were not skewed around the mean, it was deemed appropriate to employ a normal (Gaussian) distribution to characterise these coefficients. Milne et al. (2014) also followed this approach using data from Penman et al. (2000). Milne et al. (2014) chose to interpret the min-max range as a 95% CI to allow the use of an unbounded distribution, and the same approach was followed here.

7.2.2.2. N_2O and CO_2 from managed soils

Uncertainties for emission of N_2O and CO_2 from soils were characterised using data from de Klein et al. (2006)[15]. All nitrous oxide emission factors show a positive (right-tailed) skew. This reflects the pattern typically observed in measurement of N_2O emissions (e.g. Rees et al., 2012). Previously, some authors (e.g. Milne et al., 2014) have chosen to characterise this using a lognormal distribution, whilst others (e.g. Gibbons et al., 2006) have used triangular distributions.

Uncertainty statistics were presented for N_2O in the form of a best estimate with minimum and maximum bounds (de Klein et al., 2006; Dong et al., 2006). Whilst the triangular distribution is more straightforward to parameterise with these data, the increased weight this type of probability density function (PDF) puts on the distribution 'tails' can lead to under-representation of the best estimate in the Monte Carlo analysis, and subsequently to systematic bias where the distributions are skewed. It was therefore decided to follow the approach of Milne et al. (2014) and to utilise a lognormal distribution to represent uncertainty associated with nitrous oxide emission factors.

The IPCC methodology for the calculation of N_2O emissions from soils and manure systems also include other coefficients, in addition to the emission factors (designated

[15] The United Kingdom has recently developed a Tier 2-level methodology for this emissions source (Chadwick et al., 2016), reducing epistemic uncertainty associated with this variable. However, this was not available during the development of this modelling approach.

$EF_{1,\ 2,\ etc.}$) which are discussed above. These coefficients are associated with the processes leading to the indirect emission of N_2O (namely volatilisation and leaching) and denote the fractions of N from a particular pool which are transported by these processes (Dong et al., 2006; de Klein et al., 2006).

Uncertainty statistics are presented for these coefficients in the form of a best estimate and range, as above. However, given that these coefficients do not represent the emission of N_2O (but rather the processes which lead to this), there is no theoretical justification for reconciling these values to a lognormal distribution. The given minimum and maximum values also exhibit highly variable skew between coefficients, suggesting that an unskewed distribution would not be appropriate. Milne et al. (2014) applied a Beta distribution to these coefficients, and a similar approach was chosen here.

The PERT distribution (also called Beta PERT) is a derivative of the Beta distribution, and is designed specifically for the purpose of modelling expert estimates (Clark, 1962). As such, it follows the basic format of a Beta distribution, but employs a best, minimum and maximum estimate as distribution parameters. It was chosen for this purpose as it represents an advantage over the simpler triangular distribution through lower weighting of the distribution 'tails', and hence lower likelihood of systematic error where distributions are skewed. A PERT distribution was also deemed most appropriate for EFs denoting CO_2 emissions as a fraction of applied lime and urea.

7.2.2.3. Crude protein and digestible energy

Dietary digestible energy (DE%) and crude protein content (CP%) are required inputs for the IPCC Tier 2 calculation of enteric methane, manure methane, and manure nitrous oxide (Dong et al., 2006). Digestible energy directly impacts enteric CH_4 emissions and manure production quantity (which in turn impacts emissions of manure CH_4 and N_2O); dietary CP% scales manure nitrogen content, which directly scales N_2O emissions. Dietary DE% and CP% are calculated in AgRE Calc as described in section 3.1 of this thesis; this section describes the characterisation of uncertainty in this process.

Feedipedia (INRA, 2012) was used to supply estimates of the standard deviation for the DE% and CP% of fed rations by individual ration component. Standard deviations were also sourced for the gross energy (GE) and dry matter (DM) content, also used in the calculation of dietary characteristics for the fed ration (see section 3.1 for full methodology). For grazed grass, the model described in chapter five of this thesis was used to provide an estimate of standard deviation for DE% and CP%. Values for ration component DE% and CP% are given in the appendix (section A.1). For all aspects of the ration, there was no evidence to suggest that skew existed in any of the dietary parameters, and so a normal distribution was employed to characterise these. The DE, CP and DM parameters are employed in the modelling process as percentages (DE as a % of GE, CP as a % of DM, DM as a % of fresh weight) and so the distributions were bounded at 0 and 100% to ensure stochastically sampled values would remain within this boundary.

7.2.2.4 Production of agrochemicals

Emissions from production of fertilisers were characterised in the model using emission factors, specific to western Europe, as presented by Kool et al. (2012). The authors also supplied an estimated minimum and maximum value for each EF; given variable direction of skew, a Beta PERT distribution was chosen to characterise these. Pasture in the modelled system was treated with NPK fertiliser with an embedded emission factor of parameters *min* = 3.05, *B.E.* = 5.62, *max* = 7.27 kg CO_2-eq kg N^{-1}.

For the production of herbicides, AgRE Calc utilises mean emission factors calculated from data provided by Audsley et al. (2014). To provide an estimate of uncertainty in the emission factor for herbicide applied to pasture, the range of the Audsley et al. (2014) dataset for herbicides was used to provide a minimum and maximum emission factor estimate. Given the relatively small size of the dataset (N = 37), a limited amount could be inferred about the shape of the distribution; as such, a uniform distribution of parameters *min* = 7.38, *max* = 47.68 kg CO_2-eq (kg active ingredient)$^{-1}$ was defined for herbicide production.

7.2.2.5 Emissions from fuel and electricity

For emissions from electricity production, AgRE Calc makes use of emission factors provided by GHG Protocol (2012). This database does not provide a *de facto* estimate of uncertainty in the emission factors provided, so the range of values given for emission factors from 2000−2012 was employed to provide an estimate of variability. A Beta PERT distribution of parameters *min* = 0.44, *B.E.* = 0.48, *max* = 0.51 was therefore employed to characterise uncertainty in electricity production, with the best estimate (B. E.) corresponding to the most recent (2012) emission factor

For emissions from diesel use, a similar approach was followed, utilising EFs from the DEFRA/DECC Conversion Factors for Company Reporting. For the best estimate, the 2015 EF was utilised, with uncertainty stemming from the range 2012−2015. This resulted in a Beta PERT distribution of parameters *min* = 3.17.44, *B.E.* = 3.17, *max* = 3.25 kg CO_2-eq litre^{-1}.

7.2.2.6 Production of livestock feeds

All feed with the exception of grazed grass was modelled as being produced off-farm; whilst some feeds, particularly roughage, would typically be produced on-farm, this approach a) ensured the use of nationally representative production practices and avoided biasing the estimate through adherence to a farm-specific production strategy, and b) allowed this the epistemic uncertainty in feed production practices to be accounted for. As a consequence of this approach, and to avoid biasing the estimate, transport emissions for roughage feeds were excluded from the footprinting process. As discussed in the introduction to this section, where variability in production practices takes place outside the modelled system (i.e. in the production of imported livestock feed), this would be treated as an epistemic uncertainty with respect to the production system in question.

The flexibility of the sub-model developed for calculation of embedded emissions in livestock feeds (the development of which is described section 3.2.2) permitted the adaptation of this approach to the Monte Carlo simulation in question. The activity data collation described in data 3.2.2 included estimates of uncertainty for cultivation parameters (primarily yield, agrochemical application rates, and processing inputs), and the feed emissions sub-model was expanded to incorporate these. The components of some feeds, particularly concentrates, were produced outside of the country of simulation; the collated FeedPrint dataset accounts for this, and provides country-specific activity data. Where country of production or processing was variable, this was accounted for, and was modelled as a stochastic element in the simulation.

The coefficients in the feed emissions sub-model itself were also transformed into stochastic parameters. Nitrous oxide emissions from crop residues, fertiliser application, and manure application were calculated, as in AgRE Calc, using emission factors from de Klein et al. (2006). These varied depending on country of production, and this was accounted for. Carbon dioxide emissions from lime and urea were calculated according to the same methodology, and uncertainties were characterised concurrent with the approach defined in section 7.2.2.2. Emissions from electricity, fuel and agrochemical use were calculated using the same sources and uncertainty as AgRE Calc (sections 7.2.2.4, 7.2.2.5). Note that for electricity and agrochemicals, country of production impacts the choice of emission factor. Emissions from production of hexane, a solvent used in feed processing (the only emissions source not considered in AgRE Calc), were modelled using a Beta PERT distribution of parameters *min* = 0.31, *B.E.* = 0.62, *max* = 0.93 kg CO_2-eq kg^{-1} as in the FeedPrint methodology (Vellinga et al., 2013).

7.3. Results

7.3.1. Simulation results and uncertainty analysis

The simulated system produced a total of 12.22 ± 1.58 tonnes CO_2-eq annually[16]. Total production output was 1 finished steer sold for slaughter, at an average live weight of 600 kg, and cull beef at 0.07 head of cull cows and 0.013 head of cull bulls, equating to 64 kg of LW. Of the total live weight produced by the system, 90.4% was finished beef and 9.6% was cull beef.

Calculated deterministically, the emissions intensity of the beef production system as a whole was estimated at 17.73 kg CO_2-eq kg LW^{-1}. Calculated stochastically, the mean

[16] Note that due to the nature of the modelled system, some systematic discrepancy was evident between deterministically and stochastically calculated values. In the following section, unless otherwise specified, quoted values refer to stochastically calculated results. Also, unless otherwise specified, values given as ± represent one standard deviation.

production emissions intensity was higher at 19.20 ± 2.49 kg CO_2-eq kg LW^{-1}, as the distribution of the stochastically calculated results was positively skewed (*skew* = 0.95) (Fig. 7.1).

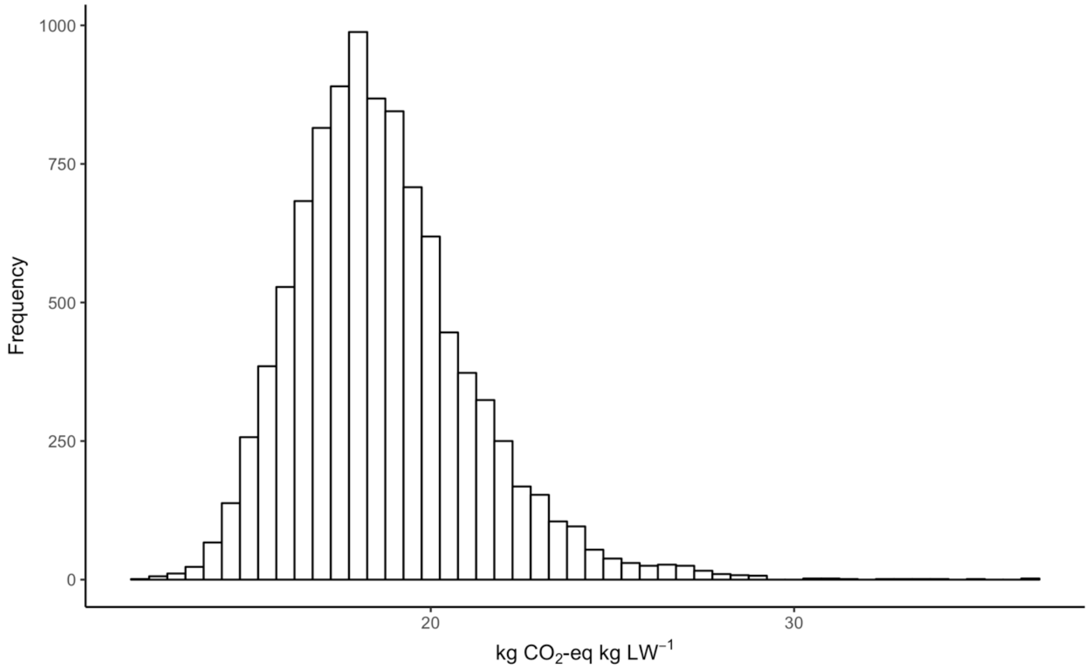

Fig. 7.1. Histogram showing distribution of stochastically calculated emissions intensity for the modelled system. Total frequency = 10,000. Note that the distribution exhibits a positive skew (skewness = 0.95), leading to the difference between the deterministically estimated E.I. (17.73) and stochastically calculated mean (19.20).

Breaking down the system emissions into source categories (Fig. 7.2), the emissions intensity of production for the system was found to be dominated by CH_4 emissions from enteric fermentation, which accounted for 48.3% of the deterministic total and 44.9% of the stochastic total. The three largest categories (enteric fermentation, feed production and manure deposition) between them accounted for 84% of the total footprint. Methane (from manure and enteric fermentation) accounted for just under half of total emissions (in CO_2-eq), whilst N_2O accounted for approximately one third (Fig. 7.2).

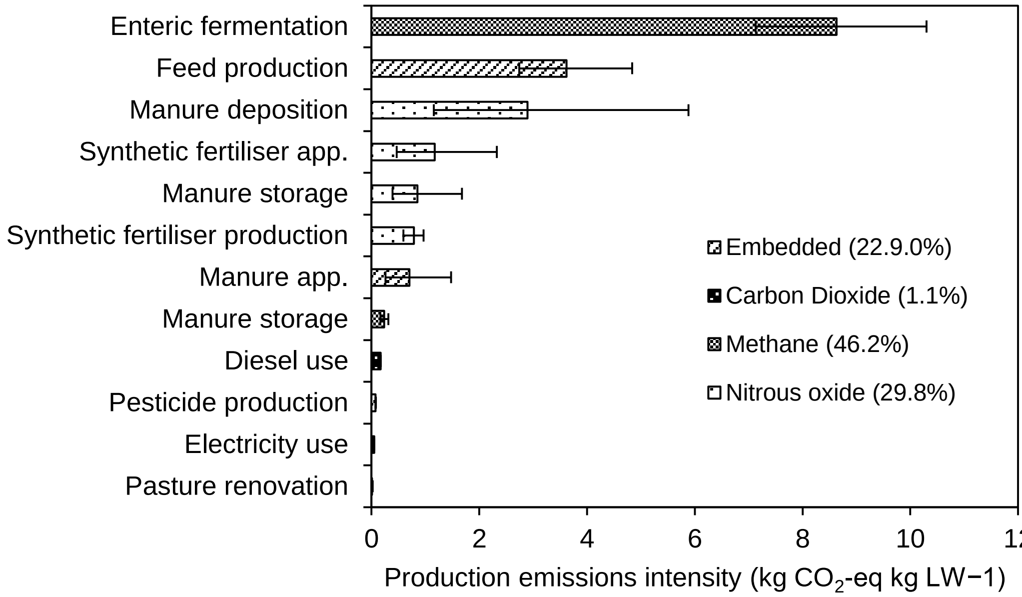

Fig. 7.2. Breakdown of the total emissions intensity estimate (calculated stochastically) to the level of individual emissions sources. Error bars indicate 5–95% *CI* for each source, calculated via Monte Carlo simulation. Asymmetry in the 5−95% *CI* results from skewness in the modelled uncertainties, primarily for N_2O emissions. Total % breakdown by gas (for mean values) is given in parentheses in the legend.

Contribution to the overall uncertainty in the emissions total varied considerably by emissions type (Fig. 7.3). Nitrous oxide emissions were most variable despite being lower in magnitude than CH_4 emissions. Embedded emissions showed similar uncertainty to CH_4 emissions, though both N_2O and embedded emissions showed a strong positive skew. Methane emissions were relatively unskewed.

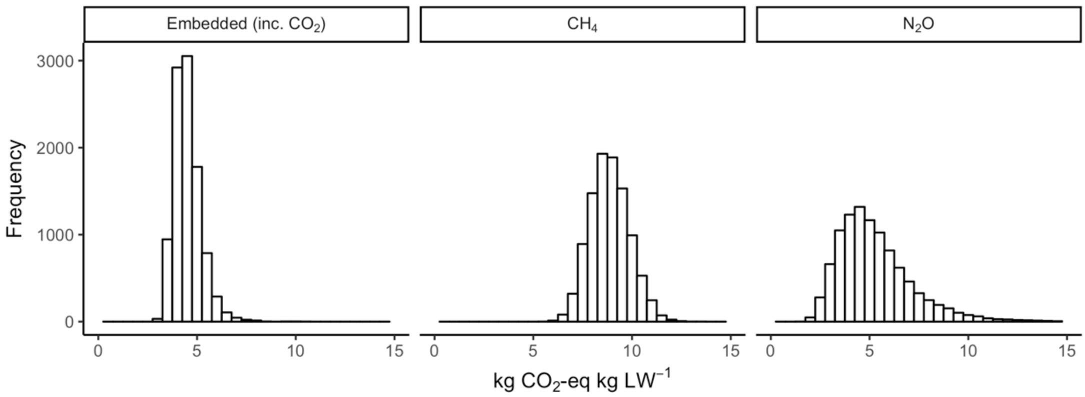

Fig. 7.3. Histograms showing uncertainty and distribution for different emissions types. Total frequency = 10,000. Note that CO_2 emission factors for diesel use are incorporated into the embedded emissions estimate due to their small overall magnitude and variability.

Table 7.1 presents a breakdown of the components of the footprint and explores the discrepancies between the deterministically and stochastically calculated estimates. Emissions from the system as a whole demonstrate considerable positive skew, meaning that the modelled mean emissions are 8.3% higher than the deterministically calculated estimate. Breakdown of this value into component emission sources shows that this positive skew stems from emissions of nitrous oxide; emission factors for these components of the footprint were modelled to follow a lognormal distribution. Mean emissions of nitrous oxide are 20−40% higher for the stochastically modelled system in comparison to the deterministic estimate.

By contrast, CH_4 emissions from enteric fermentation and manure storage are unskewed, and the stochastically calculated mean did not differ systematically from the deterministic estimate. Uncertainties as a fraction of the mean were lower for CH_4 emissions in comparison to N_2O, but the more emissions overall in this category meant that overall these uncertainties were of a similar magnitude to N_2O uncertainties. Emissions from production of feed showed significant uncertainty and a positive skew, whilst fertiliser production emissions were negatively skewed, rendering the calculated mean lower than the deterministic estimate. Uncertainty in fertiliser production emissions was low in comparison to other sources, however. Emissions from fuel and electricity use made relatively small contributions to the overall EI and uncertainty, and were not skewed.

Table 7.1. Breakdown of emissions estimates into source categories based on deterministic and stochastic calculation approaches.

		Deterministic model output (kg CO_2-eq kg LW^{-1})	Stochastic model output (kg CO_2-eq kg LW^{-1})		Confidence interval		% discrepancy (deterministic - stochastic)
			Mean	St. dev.	5%	95%	
Pasture renovation	N_2O	**0.01**	**0.01**	**0.01**	**0.00**	**0.02**	**−32.1%**
Fertiliser application	N_2O	**0.88**	**1.17**	**0.66**	**0.47**	**2.33**	**−33.4%**
Manure application	N_2O	**0.49**	**0.70**	**0.41**	**0.26**	**1.48**	**−43.6%**
Manure storage	N_2O	**0.69**	**0.85**	**0.48**	**0.39**	**1.68**	**−23.0%**
Manure deposition	N_2O	**2.23**	**2.90**	**1.55**	**1.15**	**5.88**	**−30.1%**
Enteric fermentation	CH_4	**8.56**	**8.63**	**0.97**	**7.13**	**10.30**	**−0.8%**
Manure storage	CH_4	**0.23**	**0.23**	**0.05**	**0.16**	**0.31**	**−2.3%**
Diesel use	CO_2	**0.08**	**0.08**	**0.00**	**0.07**	**0.08**	**0.4%**
Electricity use	CO_2	**0.17**	**0.17**	**0.00**	**0.17**	**0.17**	**−0.4%**
Fertiliser embedded	CO_2-eq	**0.81**	**0.79**	**0.11**	**0.59**	**0.96**	**2.7%**
Feed/bedding embedded	CO_2-eq	**3.54**	**3.62**	**0.68**	**2.74**	**4.84**	**−2.3%**
Pesticides embedded	CO_2-eq	**0.05**	**0.05**	**0.00**	**0.05**	**0.05**	**0.0%**
Total system emissions intensity	CO_2-eq	**17.73**	**19.20**	**2.49**	**15.69**	**23.70**	**−8.3%**

7.3.2. Sensitivity analysis of system emissions intensity

A sensitivity analysis identified a total of 76 coefficients and emissions factors (with associated probability distributions) which impacted the result of the stochastic model calculations. These coefficients, together with their distributions, descriptions and sources, are highlighted in table A.1 (appendix).

Providing an initial assessment of the propagation of uncertainty through the model as a whole, Fig. 7.4 shows the influence on conditional mean emissions intensity of individual coefficients ranked in order of influence. The variation in sensitivity of the conditional mean to a coefficient derives jointly from a) the role of the coefficient in the model, and b) the uncertainty surrounding it. Fig. 7.4 shows that the vast majority of the uncertainty in the modelled emissions intensity is derived from uncertainty in 10−15 coefficients; for coefficients ranked lower than this, the impact on the conditional mean levels off at < 0.5 kg CO_2-eq kg LW^{-1}. As such, these coefficients represent the 'low-hanging fruit' in terms of improving the ability of the model to accurately and precisely predict emissions from livestock production.

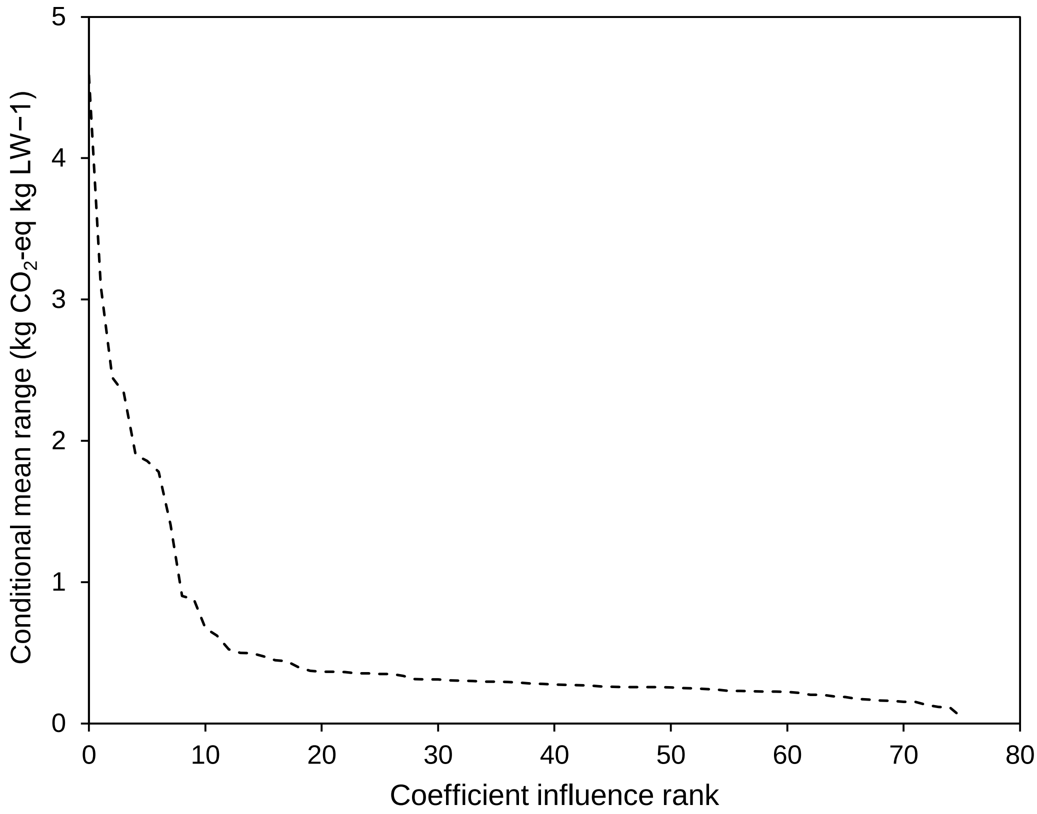

Fig. 7.4. Scree-type plot showing conditional mean range (production emissions intensity, in kg CO_2-eq kg LW^{-1}) plotted against sensitivity ranking for disaggregated coefficients.

Based on this intial assessment, the impact of the fifteen most important coefficients in terms of contribution to modelled uncertainty were analysed in greater detail. Coefficients were aggregated where necessary to avoid multiple iterations of a similar parameter in the analyses, and the conditional mean for the aggregated coefficients plotted over a 90% confidence interval (Fig. 7.5). Accordingly, the resulting 'tornado plot' shows the impact of each of the 15 highest ranked coefficients on the calculated conditional mean emissions intensity. Table 7.2 provides greater detail on the role and values of the modelling coefficients presented in Fig. 7.5. Together, these coefficients explained 77.9% of the variability in the stochastically calculated emissions intensity for the modelled system.

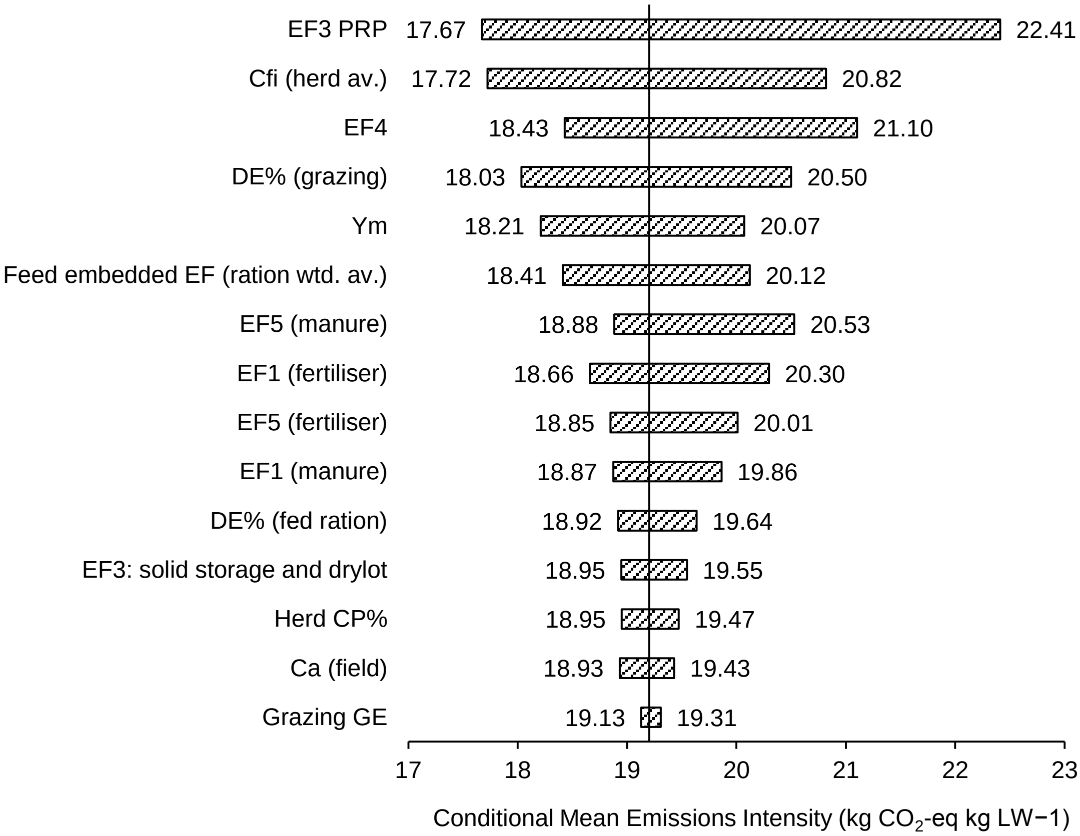

Fig. 7.5. Tornado plot presenting the impact of the 15 most influential modelling uncertainties on the calculated mean emissions intensity. Conditional mean is given to 90% confidence interval (i.e. 5−95%). The y-axis intersects at the calculated mean emissions intensity (19.20 kg CO2-eq kg LW−1). See table 7.2 for coefficient definitions.

Table 7.2. Values and descriptions for most influential modelling uncertainties in the calculated production emissions intensity for the modelled beef system.

Emission type(s)	Parameter	Distribution type	Mean ± std. dev.			Description
N_2O	EF_{3PRP}	Lognormal	0.02	±	0.01	Fraction of nitrogen in manure deposited by livestock on grazing ground which is directly emitted as N_2O
CH_4/N_2O	Cf_i (herd av.)[a]	Normal	0.32	±	0.05	Net energy for maintenance (NE_m) required by livestock, in MJ kg LW^{-1} day^{-1}
N_2O	EF_4	Lognormal	0.01	±	0.01	Fraction of volatilised nitrogen from manure deposited/spread on grazing land emitted as N_2O
CH_4/N_2O	DE% (grazing)	Calculated	70.95	±	4.07	Digestible energy content of the grazed diet, as a % of GE
Embedded	Feed embedded EF (ration wtd. av.)	Calculated	707.50	±	273.70	Weighted average embedded emission factor for purchased livestock feed, in g CO_2-eq kg FW^{-1}
N_2O	EF_5 (manure)	Lognormal	0.01	±	0.00	Fraction of leached nitrogen from manure deposited/spread on grazing land emitted as N_2O
CH_4	Y_m	Normal	6.50	±	0.51	Enteric methane emission factor for all cattle, % of gross energy intake released as methane
N_2O	EF_1 (fertiliser)	Lognormal	0.01	±	0.00	Fraction of nitrogen in applied synthetic fertiliser which is directly emitted as N_2O
N_2O	EF_1 (manure)	Lognormal	0.01	±	0.00	Fraction of nitrogen in spread manure which is directly emitted as N_2O
N_2O	EF_5 (fertiliser)	Lognormal	0.01	±	0.00	Fraction of leached nitrogen from synthetic fertiliser applied to grazing land emitted as N_2O
CH_4/N_2O	DE% (fed ration)	Calculated	62.99	±	1.34	Digestible energy content of the housed diet, as a % of GE
N_2O	EF_3 (solid storage and drylot)	Lognormal	0.01	±	0.00	Fraction of nitrogen in manure stored in solid storage which is directly emitted as N_2O
CH_4/N_2O	C_a (field)	Normal	0.17	±	0.03	Ratio of net energy for activity (NE_a) to net energy for maintenance (NE_m) (all cattle)
N_2O	Grazing CP%	Calculated	15.95	±	0.52	Crude protein in the grazed diet, as a % of DM
CH_4/N_2O	Grazing GE	Normal	18.30	±	0.38	Gross energy in the grazed diet, in MJ kg DM^{-1}

[a] The given Cf_i value of 0.322 is raised by 20% for lactating females and by 15% for intact males (Dong et al., 2006).

A significant proportion of the coefficients to which the modelled scenario was most sensitive were direct emission factors for N_2O (Fig. 7.5, table 7.2). Nitrous oxide made up only 29.8% of the footprint; less than CH_4 and only slightly more than embedded emissions (Fig. 7.2), though it is also worth noting that a significant proportion of embedded emissions in feed and bedding was N_2O. The positive skew observed in the final result, and to a large extent the discrepancy between the deterministically and stochastically modelled emissions intensities, can be explained by the strong influence of these variables.

Uncertainties in the IPCC Tier 2 energy calculations for livestock (Dong et al., 2006) also contributed significantly to the footprint uncertainty. The calculated energy requirements of livestock are used in the calculations to estimate the gross energy intake of each class, which impacts the resulting enteric CH_4 emissions and manure production. The parameter in this calculation to which the model was most sensitive was Cf_i, a coefficient denoting the estimated maintenance net energy (NE_m) requirements of different livestock classes. A number of additional components of this calculation (NE_p, NE_a) are scaled by the calculated NE_m, which contributes to the influence of this coefficient. The coefficient C_a, which scales the calculation of net energy for activity (NE_a), is also influential in the modelled uncertainty (Fig. 7.5).

The coefficient Y_m also forms part of this calculation, and represents the percentage of gross energy which will be converted to enteric methane. Given the relatively high uncertainty in this coefficient, and the direct relationship it has with enteric methane emissions, it is unsurprisingly important in its contribution to modelling uncertainty.

Coefficients relating to manure production, such as the CP% (crude protein %) and GE (gross energy) of grazing also showed an important impact on the footprint (Fig. 7.5). CP% directly scales the modelled nitrogen content of manure, which itself impacts N_2O emissions from manure storage, spread and deposition on grazing land. The gross energy content of the diet is a coefficient which permits calculation of the dry matter (DM) intake from calculated gross energy requirements; this in turn impacts modelled manure production and resulting CH_4 and N_2O emissions.

Emissions from off-farm feed production formed the second largest emissions source and the fifth largest source of uncertainty of the carbon footprint of beef production for the modelled system. Assessment of the drivers behind uncertainty in this component of the footprint is complex, as the embedded emissions of production were modelled separately. To simplify the sensitivity analysis, separate emission factors were aggregated into a weighted average for assessment in Fig. 7.5. Calculated stochastically, the average emission factor per kg of feed fresh weight (FW), weighted to reflect the overall ration composition, was 360.9 ± 114.5 g CO_2-eq kg FW^{-1}.

The modelling approach assumed fixed quantities of feed, but accounted for uncertainty in a) modelled emissions and b) cultivation practices. Further analysis of the drivers behind the uncertainty in the average EF shows that emissions from production of concentrate feeds (e.g. maize gluten, concentrates) were among the largest per kg of feed, and also showed some of the highest uncertainties (Fig. 7.6). Given the high proportion of silage in the diet, however, emissions from off-farm silage production represented the largest source of feed-production emissions, and the largest uncertainty. Silage has a low DM fraction in respect of other feedstuffs, meaning the water content and emission factor per kg FW is lower, but its inclusion as FW in the diet is higher in comparison to drier roughages.

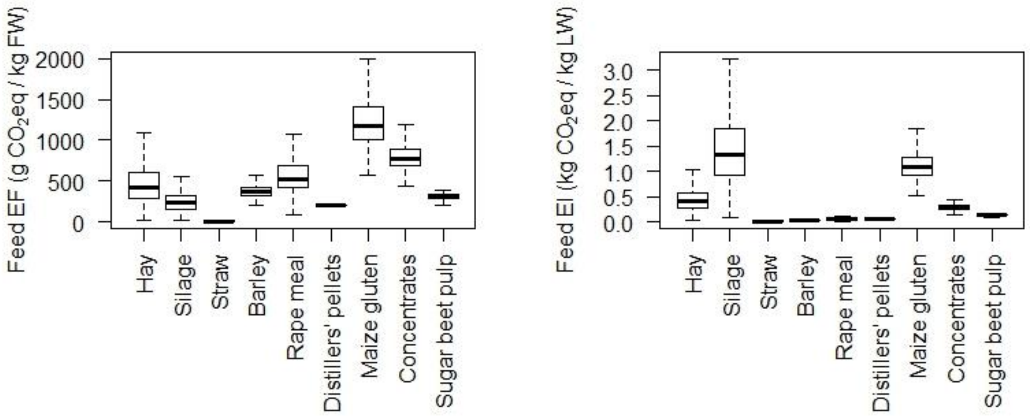

Fig. 7.6. Uncertainty in calculated emission factors (left) and emissions intensity (right) for off-farm feed production in the modelled beef system (FW = fresh weight of feed, LW = live weight of beef produced).

Of the non-roughage feeds, lowest emission factors and uncertainties were shown by byproduct-based feeds such as sugar beet pulp and distillers' pellets (Fig. 7.6). In these cases, cultivation emissions were allocated to the primary co-products (sugar and alcohol respectively), meaning that remaining emissions (and accompanying uncertainty) stemmed solely from the processing and transport sectors. This is the approach employed by Vellinga et al. (2013), and is justified by economic allocation; the economic value of the co-products in these cases is deemed to be negligible or zero prior to transport and processing.

7.4. Discussion

This study is unique in identifying and quantifying the root causes and impacts of uncertainty in an IPCC Guidelines-based LCA of suckler beef production. Whilst the narrative developed here is, to some extent, specific to the modelled system, it is also generalisable in many respects to the majority of pasture-based northern hemisphere suckler beef systems, including major GHG contributors such as western Europe, the US and Canada.

IPCC N_2O and CH_4 emission factor uncertainties have been identified as important in national inventory calculations for agriculture in the United Kingdom (Milne et al., 2014) and Canada (Karimi-Zindashty et al., 2012), but as national-level assays, these calculations are differently scoped, and crucially differ from the present assessment in that they do not permit the holistic calculation of an emissions intensity of production for a particular commodity. This study found that uncertainties in N_2O emission factors (relating primarily to emissions stemming from manure and fertiliser application) are of greatest importance in a suckler beef system, and any effort to refine these which reduces uncertainty in field-based N_2O emissions would significantly improve confidence in modelled estimates of emissions intensity for beef production. Recent improvements in methodology used by the UK government for reporting agricultural N_2O (Chadwick et al., 2016) reflect the importance of uncertainty in this variable to many aspects of agricultural emissions.

Of all nitrous oxide emissions in the modelled system, emissions stemming from manure were of greatest importance to the overall footprint, and hence the emission factors associated with this variable were of greatest consequence to uncertainty in the modelled system. Secondarily to direct N_2O emission factors, decreased uncertainty in coefficients which impact modelled manure production volume (livestock GE requirements, GE of diet, CP% of diet) would also greatly increase confidence in calculations of emissions from this source.

In particular, grazing gross energy, which scales the calculation of manure production volume for this period, was an influential factor. For the modelled scenario, this coefficient for grazed grass was taken from measurements made by Stergiadis et al. (2015) with a relatively low standard deviation of around 2.1%. The IPCC guidelines (Dong et al., 2006) provide a generalised GE estimate for all feed types which has a much higher uncertainty of 8% (Monni et al., 2007); given the influence of this variable in the modelled system even with lower uncertainty, the argument can made for a further refinement of this estimate where possible.

Enteric CH_4 emissions formed a significant proportion (47.5%) of the overall system emissions. Uncertainty relative to the overall magnitude of this emissions source was lower in comparison to N_2O emissions, but remains of considerable importance given the relative contribution of CH_4 to the footprint. The coefficient Cf_i (animal maintenance energy, in MJ kg body weight^{-1}) was found to be the most influential coefficient in this calculation chain, and second most important uncertainty overall. For simplicity in the broader sensitivity analysis (table 7.2, Fig. 7.5), this coefficient was calculated as a herd average; disaggregation of this showed that the Cf_i for lactating suckler cows was the most influential iteration of this coefficient. This is likely to be due to both the maintenance energy requirements per head for this class and the large number of animals in this class required in the overall herd structure (see table 7.2). Adding to the influence of this coefficient, calculations of net and gross energy are used to scale not only enteric CH_4 emissions, but also manure production volume, which in turn scales emissions of N_2O and CH_4 from manure. This finding backs those of Karimi-Zindashty et al. (2012) and Milne et al. (2014) at national level.

The coefficient Y_m was also found to have significant impact on the uncertainty in emissions (table 7.2, Fig. 7.5). Y_m is an emission factor for enteric CH_4, denoting the percentage of calculated animal gross energy intake which is released as methane. The use of a fixed value for Y_m has come under criticism by some authors (e.g. Smith et al., 2015), and the IPCC acknowledge some limitations; GE intake affects the Y_m percentage (this is partly accounted for by the revision of Y_m to 4% for feedlot cattle on >90% concentrate feed), as do factors such as heat or cold stress and variations in rumen fauna (Röös & Nylinder, 2013). Refinement of this approach such that uncertainty in Y_m is reduced would serve to reduce uncertainty in the calculated emissions from the production system; however, this study shows that uncertainties in the calculation of gross energy requirements must also be addressed.

The holistic nature of the approach means that these epistemic uncertainties were considered alongside uncertainty in embedded emission factors for commodities used in the production process; this is a key element which differentiates this approach from national-level inventories (e.g. Karimi-Zindashty et al., 2012; Milne et al., 2014). This uncertainty differs in that it encompasses both epistemic uncertainty, as considered for the modelled production system, and uncertainty resulting from variability in production practices. This study finds that emissions from the production of livestock feed form both a substantial component of the footprint (the 2nd largest category after enteric emissions), and a large contributor to uncertainty within the calculated overall emissions from the production system.

Of the disaggregated emission factors presented in Fig. 7.6, the highest uncertainties were found in the production of processed feeds such as maize gluten and compound concentrates. However, owing to variability in grassland management practices, hay and silage emission factors also showed considerable uncertainty. Given the prevalence of these roughages in the modelled diets, these uncertainties had the greatest impact on the overall contribution to the emissions intensity of production. Emission factors for production of byproduct-based feed, being composed largely or entirely of processing- and transport-related emissions, showed the lowest uncertainty.

Epistemic uncertainty in the emissions from feed production is composed to a large extent of uncertainties in N_2O emission factors. Methane emissions play a very small part in crop production (with the exception of rice, though this does not feature in the modelled system), inflating this effect. Refinement of N_2O EFs, as suggested with respect to direct emissions from the modelled system, would therefore reduce this uncertainty considerably. However, variability in production practices, yields and so on is also a major contributor to the uncertainty in emissions for off-farm feed production, and this is harder to mitigate. Improvement in crop production activity databases would reduce uncertainty, though particularly in the context of climate change, production practices are not fixed (Olesen et al., 2011), and this rate of change may represent a barrier to improvement of activity data. On-farm production of livestock feed is not uncommon, and would reduce this uncertainty; however, incorporation of this into a footprint reduces the general applicability of those results, since practices are likely to be to some extent farm-specific.

Dietary digestibility (DE%) was also shown to be represent an important uncertainty in the footprint. This study distinguished between grazing and fed rations; both were influential, though the grazing period showed the greater effect (Fig. 7.5), likely due to being slightly longer (seven vs. five months) and with greater uncertainty surrounding the final value. Milne et al. (2014) estimated 65 ± 4.98 for beef cattle ration digestibility percentage; the scope of this assessment differed in that a) the scenario modelled by Milne et al. (2014) scenario covered the full range of UK beef production strategies, and b) the uncertainty utilised by these authors represented uncertainty in ration composition as well as epistemic uncertainty in measured DE% for ration components. For the present study, the fed ration DE% was lower (62.99 ± 1.34) and the grazed DE% was higher (70.95 ± 4.07). Both uncertainties were lower than that utilised by Milne et al. (2014), suggesting that where ration composition is known (i.e. in a farm-level assessment), epistemic uncertainty can be reduced via utilisation of a modelling approach to estimate digestibility, especially in the case of the fed ration.

This has a number of implications for beef system LCAs; foremost, the recognition that the emissions intensity of production is highly sensitive to the chosen DE% value. For many studies (e.g. Pelletier et al., 2010; Cardoso et al., 2016), DE% is modelled based on a deterministically estimated value; whilst these are typically expert estimates and may be highly accurate, their adoption nonetheless means that the calculated GHG footprint is potentially subject to arbitrary influence in this respect. Often, these studies seek to compare intensive vs. extensive production systems, and it is important to recognise the impact that variations in the magnitude of estimates for this variable can make.

It also highlights an increased need for a modelling approach to be taken with respect to estimating this variable; the model used in this study to estimate grazing DE% represents a first step in this direction (see chapters five and six of this thesis). Uncertainty in this variable represents a driving factor in uncertainty in the emissions intensity of production; an improved modelling approach could a) reduce this, improving the power of LCA as a decision tool and b) provide insight into how this influential variable might be manipulated to reduce emissions in real-world production systems.

Correlation between coefficient uncertainties has been identified as a potentially important factor in the assessment of national level emissions (Milne et al., 2014). Where emissions sources are aggregated in a calculation, this can serve to increase uncertainty as estimated in a Monte Carlo simulation; where calculations are disaggregated, additive combination of uncertainties in different iterations of the same coefficient will serve to reduce modelled uncertainty (Röös & Nylinder, 2013). This study followed the approach of aggregation where possible; only one iteration of each coefficient was used for the simulation. Logically, this is justifiable in that much of the uncertainty in emission factors and other coefficients is likely to stem from spatial and temporal variability in the modelled system, which will be limited at farm level. Milne et al. (2014) suggest that IPCC publish clear guidance on how this issue should be treated in uncertainty analyses; this study backs this conclusion. In addition, given the widespread application of these national-level guidelines for smaller-scale assessments (see chapter two of this thesis; Sykes et al., 2017), it is suggested that the IPCC should make clarify this issue for application of these calculations at farm level.

More broadly, Monte Carlo simulation has been identified as a highly appropriate tool to investigate uncertainty propagation in complex models such as LCAs (Groen et al., 2014). As computational demand becomes a less limiting factor, use of Monte Carlo in livestock LCA has increased (e.g. Gibbons et al., 2006; Lovett et al., 2008; Dudley et al., 2014; Zehetmeier et al., 2014), and assessment of uncertainty in national inventory calculations for agriculture has also successfully utilised this approach (Karimi-Zindashty et al., 2012; Milne et al., 2014). This study demonstrates that characterisation of uncertainties given in the IPCC Guidelines (Dong et al., 2006; de Klein et al., 2006) for Monte Carlo simulation requires a large degree of interpretation, and some decisions required here can significantly affect results. A key example is the choice of triangular vs. lighter-tailed distributions (e.g. normal, lognormal, Beta) for skewed coefficients; different practitioners have followed different approaches here (e.g. Gibbons et al., 2006 vs. Milne et al., 2014), and given the influence of these coefficients, decisions made here can affect results considerably. It is therefore suggested that future iterations of the IPCC Guidelines be optimised for Monte Carlo simulation and contain recommendations for parameterisation of coefficient uncertainty in MCS. Furthermore, where assessments are holistic, this study demonstrates that epistemic uncertainty from emissions sources not specified in the IPCC guidelines (e.g. embedded feed production emissions) may be significant. There exists no standardised approach for the necessary combination of data sources and uncertainty in this way, and so it is important for future research to take into account the issues raised in this respect by this study.

Whilst quantification of uncertainty in farm-level GHG modelling, and LCA in general, is a relatively technical issue in many respects, it impacts the application of such approaches as a decision aid, and hence has important implications for users and policy makers. Studies have previously concluded that uncertainties in modelled GHG emissions do not greatly impact comparisons between scenarios, as similarity between scenarios and sources mean that uncertainties are likely to be highly correlated (Gibbons et al., 2006; Dudley et al., 2014). However, these studies have tended to focus on relatively similar systems; this study therefore supports this conclusion in certain circumstances, but also highlights that uncertainty in results can fundamentally affect confidence in comparisons based on trade-offs between different emissions sources; a key example would be the intensification of beef systems, where excessive enteric methane from an extensive system is substituted for N_2O from feed production to supply the requirements of an intensive one (Hünerberg et al., 2014). In such a scenario, the emissions from one system are not equivalent to emissions from another, and as such uncertainties are unlikely to be correlated. Higher uncertainties, coupled with a positively skewed distribution for N_2O emissions means that a stochastic model of this option may provide a different picture to a deterministic approach.

Finally, given the varying scale and scope of assessments for which these methods are applied, it is suggested that it may be appropriate to define ‘layers’ of uncertainty for certain influential coefficients. For example, Y_m, identified by this study and others (Karimi-Zindashty et al., 2012; Milne et al., 2014) as an important factor in the calculation of enteric methane production by ruminants, has been shown to be affected by a number of management-related and biological factors such as GE intake, heat and cold stress, and rumen microbiota (Röös & Nylinder, 2013). Each of these factors is either uncertain or has an uncertain impact on the value of Y_m, or both; division of the coefficient uncertainty into categories related to each factor would, if possible, enable researchers to make an informed choice about the scope and nature of uncertainty in a particular modelling scenario.

7.5. Conclusion

This simulation demonstrated that epistemic uncertainty in modelling coefficients relating to a) nitrous oxide emissions from manure and fertiliser, b) enteric emissions, c) embedded emissions from feed production and d) nutritional quality of the ration (especially digestibility) are highly influential in the derivation of uncertainty for a modelled suckler beef production system. These results are suggested to be for the most part applicable to northern hemisphere beef production in general, and novel in representing a holistic quantification of epistemic uncertainty for systems and models of this type.

With this in mind, LCA researchers have a responsibility to account for and effectively communicate uncertainties in modelled results. It is particularly important that issues such as systematic discrepancy between stochastically and deterministically calculated estimates (e.g. table 7.1) be communicated, and their implications made clear. Whilst the more technical aspects of the derivation of these are likely to be less accessible to non-specialist users, it is important that the implications of this are communicated effectively; in recognition of this necessity Milne et al. (2015) identify a number of methods by which this may be approached. It is equally important that the end-user of the results of such studies should be aware of the implications of this uncertainty.

To facilitate this, it is suggested that the IPCC, in the next iteration of the guidelines for national-level GHG reporting, provide guidance on the scale and scope at which uncertainties should be applied. Additionally, it is suggested that this update recognise the widespread use and proven efficacy of Monte Caro simulation as a tool for uncertainty and sensitivity analysis in this field. The availability of this base methodology would go some way towards informing and standardising approaches to Guidelines-based uncertainty and sensitivity analyses, and would greatly improve the confidence with which these models and assessments can be employed as decision-support tools in the definition of agricultural GHG mitigation policy.

Chapter Eight

Discussion and Conclusions

8.1. Conclusions based on empirical comparison of farm-level greenhouse gas accounting tools

Chapter two of this thesis (published as Sykes et al., 2017) explored the role of farm-level modelling in greenhouse gas (GHG) abatement, and showed that ostensibly similar models produce variable results from common input datasets. It was also found that even where the magnitude of the total emissions estimate is relatively consistent, there is often variance in the relative magnitudes of different emissions sources. These differences, both in both the total magnitude of the estimate, and the relative magnitude of individual sources, ranged from relatively minor to around one order of magnitude for different tools and datasets. There was also some apparent discrepancy in system boundaries, and in how emissions sources were categorised within tools.

The simplest conclusion which can be drawn from these results is that the selection of a particular tool has important consequences for resulting footprints. As such, GHG footprint calculations conducted using different tools should be compared with extreme caution, and limited emphasis can be placed on the total magnitude of estimates. The assessment conducted in chapter two also enabled some stronger conclusions to be drawn about individual tools; AgRE Calc (SRUC, 2014; Sykes et al., 2017) and the Cool Farm Tool (Hillier et al., 2011) are both relatively well documented in terms of rationale and methodology, and were relatively close in terms of results produced from common datasets. The other tools assessed (the CPLANv0 tool, the CALM tool and the CFF tool) had limited or no methodological documentation, limiting the confidence with which conclusions can be drawn. One tool (CPLANv0: SEE360, 2007) has been apparently discontinued since the analyses in chapter two of this thesis were conducted and published; it is unclear why this is the case, but it may be reflective of the overall questionable performance of the tool both in terms of empirical results, and in terms of methodological consistency and documentation.

Despite differences in the thoroughness of methodological documentation, it was possible to determine the methodology used in some cases. The IPCC (2006) Guidelines, in Tier 1 and Tier 2 variants, were found to be a very common choice for accounting for direct emissions from livestock, manure, and farmland. The analyses conducted in chapter two explored this in more detail, and found that despite a common methodological basis, differences in interpretation and adaptation of the methodology could lead to considerable differences in output. Adding to this complexity, such tools are conceptual models, and there is limited possibility to validate results against observed data. These considerations highlight the importance for tool users of recognising the differences which may be present, and for developers of thoroughly documenting assumptions made in the adaptation of any approach.

8.2. Developing farm-level greenhouse gas tools for use in policy

The review conducted in the introduction to this thesis suggested that farm-level tools may have a role in policy definition; following the insights gained in chapter two, it is possible to expand upon this narrative. This is an important consideration, given that it substantially impacts the criteria upon which tools should be judged (e.g. Colomb et al., 2012). The following section considers the potential for uptake of farm-level GHG accounting tools by policy makers, and the implications of this for developers of these tools.

While many farm level tools were initially designed for consultancy (e.g. AgRE Calc, CPLANv0), the flexibility and ease of use of farm-level GHG accounting tools gives them potential to be useful decision support tools for policy definition. As such, as the requirement to reduce sectoral emissions grows, bottom-up carbon accounting tools such as AgRE Calc (potentially in combination with subsidiary models such as the grass digestibility model developed in this thesis) are increasingly sought as auditing tools by policy makers such as the Scottish government (Hall et al., 2010; Macleod et al., 2017) and the Welsh assembly as part of the Climate Smart Agriculture project (CSA Wales, 2017). The tools in this context act to simplify the complex interactions which precipitate agricultural emissions, and fulfil a decision-support role for policy definition. It is possible that, in time, similar tools could also play a role in measurement, reporting and verification (MRV) of agricultural emissions. In either case, the role of farm-level GHG tools is changing; many (e.g. CLA, 2009; CFF, 2012) were originally developed to allow farmers, land managers and consultants to gain a better understanding of the composition and magnitude of their farm-level footprint, and are arguably best suited for this purpose. Others, which have seen ongoing development, such as AgRE Calc and the Cool Farm Tool (Hillier et al., 2011) have followed a more rigorous approach to documenting methodology, and these may emerge as better suited to application as policy-support or MRV tools. In either case, the changing role of farm-level models presents both a challenge and an opportunity for tool developers.

The key implication for tool developers is effectively the ‘stakes’ in which these models are being applied. Colomb et al. (2012) make some acknowledgment of this in their assessment of farm-level tools; some tools, the authors deem more suitable for ‘raising awareness’, while others are better suited to more in-depth assessments. Where models are used for informative or awareness-raising purposes, the stakes are low; whilst it is clearly desirable that a model should make an accurate approximation of emissions from a particular farm, the consequences of it failing to do so are intangible; crucially, no individual will suffer any direct or measurable financial loss based on the results of the footprinting process. The implications of this low-stakes situation were demonstrated by the heterogeneity of approaches demonstrable in the tools reviewed initially in section 1.3 and further tested in chapter two of this thesis (the latter published as Sykes et al., 2017). However, if policy makers choose to provide financial or market-driven incentives towards low-emitting practices, with the modelling tool used either to derive the policies themselves, to test the level of compliance of an individual enterprise, or both, the stakes at which the tool is applied are greatly raised. There are a number of implications to this transition which are considered in the following sections.

8.2.1. Model sensitivity, flexibility and data input burden

In developing the Cool Farm Tool, Hillier et al. (2011) state that an important constraint on the development was to employ methodology simple enough to keep data input burden low, but detailed enough to allow the simulation of complex scenarios and mitigation options. The development of AgRE Calc, as it has been carried out over the course of this thesis, has followed the same approach. A fundamental difference between farm-level tools (such as AgRE Calc and the Cool Farm Tool) and scenario-specific life cycle assessment (LCA) studies (e.g. Casey & Holden, 2006; Beauchemin et al., 2010; Cardoso et al., 2016) is also that tools must be flexible enough to accommodate an undefined range of scenarios and options, whilst LCAs represent only the defined scenario. Janzen et al. (2006) suggest that an important aspect of maintaining this flexibility is maintaining the interconnectivity between model processes, and this thesis echoes that sentiment. Emphasis is often put on the ability of modelling-based farm-level tools to capture the impacts of mitigation options, particularly where such tools are sought to inform policy decisions (Hall et al., 2010). Projects undertaken on behalf of governmental decision-making bodies (e.g. Macleod et al., 2017) suggest that the challenges presented to policy definition by the heterogeneity of livestock agriculture (Moran et al., 2011) could be solved with the appropriate modelling approach; however, a key component of this must be the ability to respond flexibly to a variety of scenarios.

Where LCA studies model mitigation scenarios, these scenarios tend to be modelled as an empirical calibration of the study methodology or input dataset (e.g. Cardoso et al., 2016). As already observed, LCA studies are in effect point estimates, meaning that the extrapolation of modelled mitigation options outside the defined scenario is problematic. This may be because the option itself is scenario-specific, or because the way it is captured within the methodology relies on empirical estimates which are not readily adapted outside the modelled scenario. Development of estimates for a wider range of scenarios requires considerable expertise on the part of the modeller, and a high degree of confidence that the estimates are applicable. This specificity, coupled with the heterogeneity of livestock systems, understandably represents a barrier to the incorporation of LCA-modelled mitigation strategies into policy.

The majority of the model development carried out in chapter three was designed to address this issue; an example of this is the development of a new approach towards quantifying DE% and CP% in the model (section 3.1). This means that whenever trade-offs between production of quality feed and higher enteric emissions from lower quality feed are made, the differences are captured as fully and accurately as possible, without the requirement for additional data input or empirical estimation by the user. As such, any mitigation options involving the interaction between these variables can be captured much more fully in the tool, avoiding the potential for accidental bias and negating the requirement for particular expertise on the part of the user. Linking processes in this way has been a central theme of the model development conducted in this thesis. Based on the demonstrated efficacy of these developments in the assays conducted herein, the author recommends that where farm-level models are developed for use in policy, following an approach which maximises connectivity between data processes in this way will greatly increase a model's worth in the context of policy definition.

8.2.2. Consideration of environmental data in farm-level footprint

In the context of development and improvement of farm-level models, one important issue to consider is the potential role of environmental input data. The development of the grass model (chapters five and six) represented a key example of this; in considering areas for model development, it was determined that inclusion of environmental variables such as latitude, temperature, rainfall and altitude would have the potential to considerably improve the precision and accuracy of estimates; this in turn would impact animal performance, enteric emissions, and the emissions intensity of production as a whole. An even simpler example is the IPCC Tier 2 methodology for calculation of manure CH_4 (Dong et al., 2006); modelled emissions are highly dependent on average daily temperature.

The process of making environmental variables available for use in farm-level tools would be relatively straightforward, given the availability of spatial data; from a simple input such as a postal/ZIP code, a host of spatially-explicit data can be derived to a high degree of accuracy. However, a question which must be considered is the extent to which this should be allowed to influence the calculated footprint; if financial incentives exist to reduce emissions, it could happen that certain enterprises (where unfavourable environmental conditions persist, rather than undesirable management practices) might be penalised for their higher carbon footprint.

A counter-argument to this is that the heterogeneity of farming enterprises is in part at least due to differences in environmental factors, both directly, and indirectly where environmental heterogeneity precipitates differences in management strategies. A strong argument for the usefulness of farm-level tools stems from this heterogeneity and the difficulties it engenders in defining useful policy for emissions reduction (Moran et al., 2011), so in this sense it is counter-intuitive to hamper the ability of tools to account for environmental factors. It is also valid to suggest that defining appropriate baselines, reflecting the suitability of different environments for environmentally efficient production, would go some way towards mitigating potentially unintended consequences of allowing environmental variables to influence the footprint. Finally, it should be acknowledged that identification of areas where environmentally optimal production is not possible may well be a valid and important role for tools capable of assessment at this level.

This thesis took the approach of developing a non-spatially specific tool for the reasons presented here, though advances in understanding made over the course of the thesis have highlighted the potential importance of the counter argument; namely, there exists ‘glass ceiling’ in terms of the insight that farm-level tools can give whilst assuming spatial homogeneity; the development and testing of the grassland model (chapters five and six respectively) is, again, a key example of this. As such, rendering tools spatially specific in their calculations could serve to provide much greater insight in terms of emissions mitigation, and may be necessary if policy is to be finely tuned in this respect. One solution to the potential conflict described above could be an approach which accounts for both scenarios; a non-spatially specific ‘baseline’ estimate for benchmarking, accompanied by a spatially specific footprint to give greater insight into farm- or area-specific mitigation practices. In either case, it is important to develop tools with an eye to their potential use by policy makers, and to clearly define the purpose of a particular approach to ensure it is not applied in a way which subverts its original intention.

8.3. Use of Monte Carlo simulation in farm-level greenhouse gas modelling

The introduction to this thesis identified the potential role of Monte Carlo simulation (MCS) as a tool for uncertainty and sensitivity analysis in farm-level GHG modelling. Developments undertaken throughout the thesis explored this potential and generated insight into the value of this approach. In addition, the work done as part of chapters three and seven of this thesis provides a comprehensive platform for application of Monte Carlo simulation in farm-level tools and livestock LCA studies (collated coefficient parameterisation is summarised in appendix section A.2). This section seeks to summarise and contextualise this work in relation to the extant literature, and to make recommendations for future development of this approach.

Several studies have employed MCS as an approach for uncertainty and sensitivity analyses in livestock LCA (Gibbons et al., 2006; Dudley et al., 2014), and in national-level inventory calculations (Karimi-Zindashty et al., 2012; Milne et al., 2014). No farm-level tool to date has been found which employs Monte Carlo simulation for livestock carbon footprinting. The FeedPrint tool (Vellinga et al., 2013) uses a simple MCS to assess uncertainties in the production of livestock feed, though excludes key areas of uncertainty e.g. N_2O emissions. In published studies, the application of MCS is typically the central theme of the assessment, with the objective being to focus on analysis of uncertainty or sensitivity.

Chapter seven represented a novel approach as the first study to quantitatively assess the root causes and impacts of epistemic uncertainty in a holistic LCA assessment of suckler beef production in the United Kingdom. A key finding of the study was the observation that positively skewed uncertainties (primarily relating to N_2O emissions from land) resulted in a discrepancy between stochastically and deterministically calculated emissions intensities for the system, with the stochastically calculated result 8.3% higher than the deterministic result (table 7.1). The study also identified specific coefficients relating to nitrous oxide emissions, enteric emissions, production of purchased feeds and nutritional quality of the ration as having the greatest impact on the uncertainty in calculated emissions intensity. These coefficients represent low-hanging fruit in terms of refinement of the methodologies utilised in farm-level models (see section 8.7.1 for further discussion); in many cases, this refinement will necessarily take place at a regional level.

Based on the results of this thesis, the author recommends that Monte Carlo simulation be employed routinely in LCAs of agricultural products. Gibbons et al. (2006) made the observation that uncertainty assessment can greatly increase the confidence in results generated by a system-level model, and the results of the assessment conducted in chapter seven serve to reinforce this conclusion. Additionally, the systematic discrepancy in stochastically vs. deterministically calculated results serves to highlight the importance of a stochastic assessment for completeness. Assumptions, particularly in such a heterogeneous industry, must frequently be made; whilst, for reasons of tractability, this thesis did not include a full-chapter analysis of the effects of uncertainty in input data, the variability of emissions from the hypothetical suckler and dairy systems modelled stochastically in chapter four provide a good example of the sensitivity of calculated emissions intensities to uncertainty in input assumptions. By embodying a range of values, MCS can avoid systematic, unintentional biasing of the results of LCA studies through avoidance of the requirement for a point estimate to be committed to by the practitioner. Simultaneously, the approach provides an insight into the sensitivity of the model to a particular estimated variable, giving the practitioner perspective on the relative importance of refining the estimate.

Table A.3 and equations A.1 – A.4 provide a full set of parameters and fitted/selected probability density functions (PDFs) for all of the coefficients and emission factors employed in AgRE Calc. As AgRE Calc is a farm-level model designed to encapsulate a theoretically limitless range of scenarios within the designed scope, this dataset provides a comprehensive platform for the utilisation of Monte Carlo simulation in livestock LCA and farm-level modelling. Furthermore, the methods, rationale and sources defined for the selection of these parameters (discussed in sections 3.4 and, for the specific study, in section 7.2.2) provide a blueprint for the expansion of this dataset to enable its application to a range of scenarios outside the scope of the AgRE Calc model. In addition, for modelling emissions from grass-based systems, table 5.8 provides a calculated set of parameters for grassland based on the model developed in chapter five of this thesis. This model was itself based on Monte Carlo simulation; to simplify the application of this approach, the modelled results have themselves been fitted to PDFs. As such, in addition to the scenario-based (though to some extent generalisable) conclusions drawn from the analyses carried out in chapters six and seven, this compilation of data represents an important step forward in the field of farm-level GHG modelling, and should provide a comprehensive basis for the utilisation of Monte Carlo simulation in a wide variety of livestock LCA studies.

8.4. Comparing the emissions intensities of beef finishing strategies

The analyses conducted in chapter four of this thesis served several roles in the context of the thesis aims and objectives, and of the broader literature. In respect of developments to AgRE Calc, the modelling exercise served as an exploratory process for the model development areas identified in chapter one and conducted in chapter three. In particular, the modelling exercise shed light on the critical role of grazed forage in the footprint, and served as a platform for assessment of the developments made to allow the model to account for the ration composition of individual livestock classes in the farm-level footprint (section 3.1). In the context of the wider literature, the analysis makes use of accurate and detailed activity data to conduct a highly robust analysis of the GHG emissions intensity of beef finishing strategies. This contributes original findings to the question of the emissions impacts of variation in rations and finishing strategies, and in particular provides novel insight into the temporal trajectory of emissions intensity for a variety of beef systems.

Chapter four also calculated and compared the emissions intensities of hypothetical suckler and dairy beef production systems, and linked them to calculated emissions from a live experiment comparing different finishing strategies. The study calculated emissions intensities of 14.65 –15.96 kg CO_2-eq kg LW^{-1} for finished suckler beef, and 9.36 – 10.91 kg CO_2-eq kg LW^{-1} for finished progeny from dairy enterprises. The study also compared housed, intensive finishes with a variety of extensive approaches, and found that for the modelled system, pasture-based finishes had the potential to be as or more efficient than housed, intensive approaches. Pasture-based finishes were typically longer and ultimately heavier, and in the case of suckler beef progeny, this represented a more effective return on the emissions load from the parent system. Performance differences between individuals were also lower for pasture-based finishes, with the faster-growing housed groups showing greater individual variation in response to the treatment.

The assessment also served to highlight the critical consideration of dietary digestibility and crude protein in the carbon footprint of production. Given that the performance of the animals is likely to greatly reflect this, it also forms a crucial component of the trade-off between better performing livestock and greater emissions from production of high quality feeds. A model which could not account for this intricacy of the modelled systems would have limited ability to make robust comparisons. Of the farm-level models compared in chapter two, only AgRE Calc and the Cool Farm Tool had the ability to modify modelled enteric or manure emissions based on data relating to dietary quality. Accordingly, this assessment serves as proof of the value of this approach, and the implementation of an identical or similar methodology in farm-level GHG accounting tools (and potentially also in livestock LCA) is recommended based on the analyses conducted here.

Comparisons made in the literature between extensive and intensive approaches are often close in terms of the difference in magnitude of emissions, though more recently, prevailing opinion has tended towards intensification of practices (e.g. Pelletier et al., 2010; Cardoso et al., 2016). The conclusions drawn as a result of the analyses conducted in this thesis do not directly contest the validity of these conclusions, but serve to present an alternative scenario to the housed, intensive finish, which has potential to preserve the benefits of extensive systems, whilst maintaining a comparable or better carbon footprint. These benefits, though not typically included in GHG accounting methodologies (and, for this reason, excluded from quantitative assessment in this thesis) may be emissions-related in terms of soil carbon sequestration by productive grassland (Ostle et al., 2009; Rutledge et al., 2017a, 2017b), or protection of existing soil carbon through prevention of conversion of high-quality grazing land to arable cropping. There may also be tangible benefits in terms of ecosystem services provided by pasture land (Swinton et al., 2007), animal welfare standard may be higher than for housed animals (Wilson et al., 2002; Zhang et al., 2007), and grass-fed beef may be seen by the consumer as healthier or higher quality (Nuernberg et al., 2005).

The analyses conducted in chapter four of this thesis also serve to highlight the usefulness of low-granularity input data in generating robust and statistically comparable results from farm-level modelling assessments. In particular, the availability of individual animal-level performance data allowed the analyses to provide novel insight into within-group variability to treatments. This is rare in LCA literature; a recent study by McAuliffe et al. (2018) is a notable example of individual-level livestock LCA. Temporal stratification of the activity data also enabled novel insight into the way in which the emissions intensity of production can vary between grazing and housed periods. The value of this highly detailed input data is clear; however, LCA practitioners are likely to utilise the most detailed activity data available, so a recommendation to source high quality data is largely a moot point. Rather, it is worth pointing to some of the lessons learned from the availability of this high quality data; namely, that variations in dietary quality and performance, even in a tightly controlled experimental environment, are possible between both individual animals and time periods, and these can substantially impact the footprint. Based on the analyses conducted here, it is recommended that these factors be accounted for where possible, either quantitatively or qualitatively. Monte Carlo simulation, as utilised to model the hypothetical parent systems for this analysis, may be of use in dealing with areas where data detail or quality is lacking.

8.5. Characterising the nutritive value of grazed forage in greenhouse gas models of ruminant production systems

8.5.1. Findings from this thesis

In making the comparison between intensive and extensive production systems, chapter four of this thesis demonstrated the sensitivity of the production footprint to the nutritional value of grazed grass; this observation stands particularly for extensively finished beef, but in either case, suckler and dairy systems which provide beef cattle for finishing systems of all types are highly dependent on grazing as a source of nutrition. Chapter four demonstrated that the reliance of beef systems on this factor is compounded by a number of further elements, namely a) the nutritive variability of grazed grass as a feed source, and b) the sensitivity of livestock performance and direct emissions to this variability. While the data collated for chapter four's analyses included scenario-specific laboratory estimates of grazing digestibility, this is unlikely to be the norm for a typical system; thus, it threw into sharp relief the lack of framework for estimating the parameters which characterise this factor in the commonly used IPCC Tier 2 methodology (Dong et al., 2006), upon which AgRE Calc relies.

Further investigation (section 5.1) confirmed that this lack of framework means that digestibility values for grazing land tend to be arbitrarily estimated in the majority of LCA studies, national inventory assessments, and farm-level tools which employ the IPCC Tier 2 methodology. Given the sensitivity of the methodology to this parameter, these estimates have the potential to bias the results of the calculations; one way around this is for experts with intimate knowledge of the system in question to provide an estimated value, which provides accuracy but limits the applicability of the approach to a defined system. Particularly in the case of farm-level tools, this limit on the flexibility of the tool to capture and compare different scenarios accurately is a severe hindrance. As a result of these factors, an empirical approach to the estimation of the digestibility of grazed forage was sought; this approach was defined in chapter five and further tested and discussed in chapter six of this thesis.

The defined approach primarily utilised a regression model to predict the species composition of a grass sward based on sward age and nitrogen application rate. Digestibility estimates from the literature, standardised to a temporal baseline to reflect change in growth stages across the grazing season, were then applied to the calculated spp. composition to provide a basis for a full-sward digestibility estimate. Monte Carlo simulation functionality was integrated into the model to provide an estimate of uncertainty in the calculated values.

The model predicted that sward digestibility reduced with age and increased with higher levels of nitrogen application. The main driver of this in both cases was a greater proportion of sown spp. in the sward. The model predicted sward digestibility (digestible energy as a percentage of gross energy) varying between mean values of 71.7 ± 4.6 (one-year-old sward, 350 kg N ha^{-1}) and 67.2 ± 1.7 (25-year-old sward, 0 kg N ha^{-1}) (see table 5.8). Assessment of this approach on a modelled beef production system (chapter six) showed that the digestibility of the sward had the potential to impact cattle enteric emissions and hence emissions intensity of production.

Taking a holistic viewpoint, farm-level emissions response to the model inputs was mixed; the decreased in enteric emissions caused by reduced sward regeneration periods outweighed increases in N_2O from crop residue emissions, but increased N_2O and production emissions from fertiliser outweighed reductions in enteric CH_4 resulting from increased nitrogen application to grassland. As such, to reduce enteric emissions and increase animal performance, it would make sense to increase sward regeneration frequency to prevent the incursion of undesirable species. Addition of nitrogen fertiliser to swards may be necessary to ensure continued sward productivity and to maintain stocking rates, but is not expedient for the purposes of reducing overall production emissions. Finally, uncertainties in the model output were also used to assess the sensitivity of the beef system to this variable, and it was found that the enteric emissions intensity of beef production could vary from 10.87 – 11.86 kg CO_2-eq kg LW^{-1} (2.5 – 97.5% C.I.) as a result of modelled variation in pasture digestibility. This result suggests that this potential variability, representing the impact of additional management and environmental factors not captured in the model, could be exploited to provide further insight into mitigation strategies if the modelling approach could be extended.

8.5.2. Future development of the modelling approach

The model represents first steps in the definition of an empirical approach towards the estimation of the digestibility of grazed grass. It fulfils the aim of providing a framework to avoid unintentional arbitrary bias to this sensitive parameter, but there are a number of areas in which the approach could be improved and developed. As described in the model development rationale, the usability of the approach relies on the simplicity of required input data; as such, low-hanging fruit for model development are represented by areas where a) empirical data are available for model calibration and b) the utilisation of such data would not drastically increase data input burden.

One such example would be the inclusion of cutting regime as a management variable in the model. Ergon et al. (2016) showed that this factor can have a significant and quantifiable effect on species assemblages and growth stages in the sward. A brief review of the literature suggests that this factor may be responsible for substantial portions of the uncertainty in a) estimates of intra-specific digestibility and b) unexplained variability in sward species composition. It may be possible to quantify these impacts using existing published data, and given that cutting regimes are almost certain to be known to the system manager, data input burden would not be greatly increased.

Chapter six (section 6.5.3) also identified a number of easily-quantifiable environmental variables which could be of use to further reduce uncertainty in the model output, such as altitude, average annual or monthly temperature, rainfall patterns and soil type. Incline, drainage and aspect are also likely to play a role, though vary on a much smaller scale and hence may be more difficult to derive from a simple input dataset. However, it is worth noting that the inclusion of spatially-explicit data in farm-level models potentially engenders a number of practical and political implications, particularly where such models are used as the basis for policy definition or development of farmer incentives. These issues were discussed in depth in section 8.2.

8.6. Making decisions based on farm-level modelling approaches: Lessons from this thesis

8.6.1. Methane, nitrous oxide and carbon dioxide: Comparing apples to oranges in farm-level modelling scenarios

A great deal of GHG modelling exercises involve some element of an ‘apples to oranges’ comparison; in other words, quantitative comparison of two or more scenarios or options which have fundamental qualitative differences. An issue which falls into this category, and has been discussed at length in the literature (e.g. Shine, 2009) is the comparison of different gases. Since agricultural practices emit little CO_2, but considerable amounts of CH_4 and N_2O, this issue is especially pertinent in the case of farm-level modelling, and the research conducted over the course of this thesis highlighted some aspects of this issue which are worthy of further discussion.

The global warming potential (GWP) metric facilitates the comparison of different gases via the CO_2-equivalent unit (Manning & Reisinger, 2011), and is inherent in the AgRE Calc methodology (which utilises the GWP_{100} conversion metric). The first point to note in this respect is that the metric itself remains a subject of considerable debate, and was not even originally designed for the purposes to which it is applied today (Shine, 2009). The GWP_{100} (100 year GWP) is the most commonly used version of the metric in most types of assessment (resulting in its adoption in AgRE Calc), and it is a highly popular choice for policy makers (Manning & Reisinger, 2011) but the GWP_{20} and GWP_{500} are nonetheless equally valid approaches. However, Shine (2009) terms the adoption of the GWP_{100} an ‘inadvertent consensus’ between policymakers and the scientific community, meaning undue emphasis is placed upon it in the scientific literature. Since the different gases have different atmospheric lifetimes, the choice of timescale in the GWP is a crucial factor, and could radically impact the relative magnitude of emissions estimates for different farm-level sectors.

Many trade-offs in farm-level GHG mitigation involve the comparison of CH_4 to N_2O emissions (Hünerberg et al., 2014); these tend to take the form of substitution of excessive enteric CH_4 resulting from poorer quality ruminant diets for N_2O emitted in the cultivation of higher quality feedstuffs to improve those diets. The production system comparisons made in chapter four represent a series of points on this spectrum. Comparison of the two is wholly reliant on the much-disputed GWP metric as discussed (Smith, 2003; Shine, 2009), with the result that changes to the timescale or calculation approach for this metric would radically impact the relative magnitude of the estimates. Methane is shorter lived than N_2O, though exhibits high climate-forcing potential in its atmospheric lifetime (IPCC, 2013); as such, shorter timescales (e.g. GWP_{20}) would add weight to the GWP of methane and hence skew the comparison in favour of dietary improvement. Alternatively, a longer one (GWP_{500}) would suggest that more extensive systems, with a higher $CH_4 : N_2O$ ratio, would be more expedient.

Leaving aside the issue of emissions metrics, comparison of intensive to extensive beef production systems is in many other respects an apples-to-oranges situation. As explored empirically in chapter four of this thesis, the GHG composition of an intensive system footprint is very different to that of an extensive system. There are a number of aspects to this difference which are worth discussing.

The major difference between the two systems is that previously discussed; the substitution of enteric CH_4 (extensive systems) for crop cultivation-based emissions of N_2O (intensive systems). The first point to note in this respect is that the emissions from extensive systems occur on-farm as direct emissions from the animals in question. A considerable portion of emissions from intensive systems have the potential to occur outside the system in question in the external cultivation of livestock feeds or production of agrochemicals. In and of itself, this is not a particularly important distinction, since the impact of GHG emission is not geographically specific. However, from the perspective of making a modelled comparison of these systems, it is important to note understand the impacts of this. External emissions from the intensive system are outside of the control of the farm or system manager, meaning the activity data used to model these variables is likely to be much less certain. The methodological approach used to account for these emissions may also be subject to greater uncertainties in scope and system boundary (see section 3.3). In the vast majority of farm-level assessments, fixed emission factors are used to account for externally generated 'embedded' emissions; the use of these factors disguises the complexities behind their calculation, though it is important for practitioners and users of LCA-based assessments to be aware of this complexity. The uncertainty associated with these emission factors can often be relatively high, and was the subject of assessment in chapter seven of this thesis (further discussed in section 8.7).

8.6.2. Farm-level modelling in the future of beef production

In considering the role of farm-level footprinting tools in the future of beef production, it is important to remember that the status of beef production is not a fixed quantity, but rather that it is in constant flux. The number of cattle globally has increased by more than one-third since 1961 (FAOstat, 2017) and this trend is set to continue into the next two decades (Caro et al., 2014). The root cause of this is largely due to increases in the global human population; particularly in developing nations, this is currently rising, and is likely to continue to do so until around 2070 (Lutz et al., 2001). These same nations are also becoming wealthier, and demand for beef tracks increases in per capita GDP (Sans & Combris, 2015). These socio-economic factors lie at the heart of the global effort to mitigate emissions from production of beef.

However, at the same time, demand for meat in some developed nations, such as Germany and Japan, is dropping (FAOstat, 2017), and trends towards vegetarianism, veganism, and reduced consumption of meat tend to occur as societies develop (Ruby & Heine, 2012; Ruby et al., 2013). These trends are cultural, and relatively recent, making their relative importance something of an unknown, but in developed western nations are typically driven by perceptions relating to human health, animal welfare, or the environmental impacts of meat production (Bredahl et al., 2001; Ruby & Heine, 2012). As such, they are likely to accelerate as individuals become richer, better educated and have more leisure time. The possibility of *in vitro* cultured meat replacing livestock production systems is also present (Datar & Betti, 2010; Post, 2012), and whilst consumer perceptions are currently a barrier to large-scale uptake (Goodwin & Shoulders, 2013), this may also change as societies adjust; as such, the relative importance of the role of lab-cultured meat in future diets is difficult to predict.

Furthermore, whilst a growing population may initially be a driving factor for increased meat production, this population increase may also result in pressure to utilise agricultural land more efficiently; Cassidy et al. (2013) show that apportioning arable crop yields away from livestock and into the human diet is a viable and possibly necessary approach to feeding the projected peak population. Finally, it is worth noting that beef is also typically expensive in relation to other meats and protein sources, making it a premium product; as such, production practices tend to be of greater importance to the consumer (Mennecke et al., 2007). Grass-based production practices are likely to be seen as resulting in a healthier or higher quality product (Nuernberg et al., 2005) in comparison to housed production, and the animal welfare benefits of the former are relatively well documented (e.g. Wilson et al., 2002).

Hypothetically, then, demand for beef is likely to grow until a ‘tipping point’ is reached, where reduction of consumption in developed nations with mature markets and falling populations outweighs increases in demand from developing nations. The demographic transition model (Simpson, 2014) tracks population transition; a developing population expands as the mortality rate drops, then plateaus as the birth rate drops to equivalent levels. This is arguably analogous to the transition in demand for livestock products; demand increases as the population grows and becomes wealthier, then plateaus as social and cultural factors reduce *per capita* meat demand. Whilst growing and shrinking populations will undoubtedly play an important role in this, the influence of cultural factors, whilst hard to predict, may well be significant.

If this point is reached, global demand for beef will drop; given current production and consumption trends it is (tentatively) suggested that the peak of this trajectory will be reached in the latter half of the 21st century. It is likely, however, that at this stage, consumer awareness of production practices will be high and will continue to grow. It is argued that this lower demand, coupled with higher awareness of (and demand for) perceived product quality and desirability of production practices is likely to favour production practices which fall in the category of a ‘premium product’. If current consumer preferences and perceptions persist, it could be argued that this is likely to favour extensive production over intensive.

This has a number of implications for the role of modelling-based assessments in the future of beef production. In such a scenario, the extensive production system itself becomes as much the focus of an assessment as does the physical amount of meat produced. It may therefore make more sense to account for emissions not only in terms of quantity of product produced, but also in broader terms.

Assessing emissions per unit of live weight (kg CO_2-eq kg LW^{-1}) is a commonly used functional unit, but others are also employed in the literature. A per-kg-LW emissions intensity value has the distinct advantage that it is simple to compute and interpret, and where comparisons are made between relatively similar beef systems, it is arguably an entirely acceptable approach. Where comparisons become more disparate, however, the derivation of the functional unit must account for this. Some studies choose to compare emissions per unit of carcass weight (kg CO_2-eq kg CW^{-1}) (e.g. Beauchemin et al., 2011; Nguyen et al., 2012); this negates the impact of differences in the ratio of live weight to dressed carcass weight. Such differences are typically relatively small for beef, but such a conversion may be more useful where beef is compared to other meat products (e.g. Opio et al., 2011). Some studies go further in their comparisons of animal based products; e.g. Eshel et al. (2014) compared milk and eggs to beef, chicken and pork. To enable this, the authors utilised a number of functional units, including per calorie[17] and per g protein.

Presenting emissions only in terms of the quantity of product produced can (and has) led researchers to recommend ever more intensive production practices (e.g. Pelletier et al., 2010; Cardoso et al., 2016). These may be appropriate in some contexts, and a wide body of literature suggests that it is reasonably certain that in most cases, intensification of production is a good first step from very-low-input extensive production systems based on exploitatively-managed grassland. However, chapter four of this thesis suggests that well-managed extensive grassland can represent a better basis for production than an intensive housed system, as well as providing the additional benefits discussed. Other assessments (e.g. Subak, 1999; Casey & Holden, 2006) also point to the efficacy of extensive production. Depending on a number of environmental and management practices, extensive production may also make are use of poor-quality land unsuitable for cultivation of arable crops (Zervas & Tsiplakou, 2012), maintain that land for biodiversity and tourism (EBLEX, 2009), and provide potential for soil carbon sequestration in pastures (Subak, 1999). In essence, whilst a quantitative comparison of the two system types can be very similar, it can hide a host of qualitative differences. This does not by any means invalidate the quantitative comparison – far from it – but it is important to qualitatively assess the context of such a comparison in addition. As such, and in the context of the future of production, it is argued that the per-kg-product

[17] One calorie = 4.18 kJ.

functional unit should not be the only metric which is presented to policy makers in the context of livestock production.

The above arguments, made in the context of the analyses conducted in this thesis, suggest that a land-area based functional unit, such as kg CO_2-eq ha^{-1}, allows for the presentation of a useful metric, which would provide a basis for broadening the interpretation of the more commonly utilised product-based metrics such as per kg live weight, carcass weight, or protein. In addition, the development of robust and standardised methodologies to quantify the less tangible differences between beef production system types would be of use to modellers and decision makers. Finally, the above arguments show that it is important to realise that intensive and extensive production systems are fundamentally qualitatively different, and that socio-economic and cultural development may change the way in which beef is demanded by the consumer.

8.7. Future research and development in farm-level modelling

8.7.1. A farm-level GHG tool developer's wish-list: directions for future research and development in source methodologies

Farm-level modelling tools, such as AgRE Calc, can only be as useful as the methodologies they rely upon. In one sense, this is an obvious point, but it is important to realise that development of a farm-level GHG tool largely requires the developer to select, manipulate and apply methodological approaches, and to document the process for clarity and transparency. Innovation, in terms of collation and manipulation of background data (e.g. chapter three), is also necessary, but the tool development process rarely requires the definition of an entirely new methodological approach; the development of the grassland model (chapters five and six) is an exception in this respect. Farm-level GHG tools are also an emerging phenomenon and have rarely had modelling approaches specifically defined for them; as such, the majority (including AgRE Calc) 'scavenge' methodologies designed primarily for other approaches; the IPCC (2006) guidelines (designed for national-level GHG reporting) are a key example.

This thesis has already made the argument (section 8.1) that the IPCC should recognise firstly the role of farm-level tools in the mitigation of national-level emissions, and also the extent to which the national-level guidelines are being employed in small-scale applications like farm-level tools. Taking this a step further, and whilst recognising that the development and refinement of methodological approaches to GHG accounting requires time, expertise and funding, this section aims to build upon assessments conducted throughout this thesis to provide an overview of the areas in which developments in methodologies would most benefit the efficacy of farm-level GHG modelling approaches.

Chapter seven of this thesis, an uncertainty and sensitivity assessment of methodology used in footprinting a typical United Kingdom beef production system, served to highlight several areas which represent 'low-hanging fruit' for methodological improvement. The modelled beef system emissions intensity demonstrated a standard deviation of 12.96% resulting from epistemic uncertainty in the methodology. The uncertainties contributing to this resulted from, primarily, enteric CH_4 emissions, field-based N_2O emissions, and calculated emission factors for purchased feeds.

Field-based emissions of N_2O were shown to contribute some of the highest uncertainties to the farm-level footprint, despite being only around one-third of total emissions. The modelled system imported the majority of its feed requirements for reasons of modelling efficacy; most real-world systems would grow forage and perhaps concentrates on-farm, raising the field-based N_2O emissions and further compounding this issue. Modelling N_2O emissions from soils represents a considerable challenge (Buckingham et al., 2014), and the IPCC Tier 1 methodology (de Klein et al., 2006) used to calculate N_2O emissions was found to have very high epistemic uncertainty. Refinement of this to a more precise approach would greatly benefit uncertainty in farm-level GHG models for beef systems. In particular, it was found that further refinement of the EF_3 emission factor for direct N_2O emissions resulting from deposited manure would greatly reduce uncertainty in the overall estimate.

Enteric CH_4, calculated using IPCC Tier 2 methodology, formed the largest overall emissions source and contributed substantially to uncertainty in the overall estimate. The methane emission factor used in this approach, Y_m, has been criticised in the literature (Smith et al., 2015) and the epistemic uncertainty in this coefficient was found to be important with respect to the overall footprint. However, another coefficient (Cf_i), used to define an animal's net maintenance energy requirements in relation to its body mass, was found to be a greater contributor to the overall uncertainty. In the Tier 2 energy calculations (Dong et al., 2006), maintenance energy is used as a scaling factor for additional net energy requirements (for e.g. growth), which increases its influence. Any reduction in the epistemic uncertainty in the calculation of net energy for maintenance would therefore serve to greatly reduce uncertainty overall.

One potential route for refinement of the IPCC Tier 2 methodology could be the definition of class-specific coefficients (Y_m, Cf_i, etc.) for suckler cows. These animals form the bulk of the energy requirements for a beef production system, and even more so for dairy systems (e.g. chapter four). As such, emissions from this class contribute disproportionately to the overall system footprint. If an approach could be defined whereby a specific set of coefficients could be defined, with lower epistemic uncertainty, for suckler cows alone, this would serve to greatly reduce epistemic uncertainty in the overall estimate.

Chapter seven also found that uncertainties in emissions from the production of livestock feeds was a crucial driver of epistemic uncertainty in emission intensity of livestock production. Whilst, for reasons detailed in the methodology of chapter seven, roughage feeds typically produced on-farm were modelled as imported, the vast majority of uncertainty came from the production of concentrate feeds for the finishing stages. Drivers of this uncertainty undoubtedly include epistemic uncertainty in modelled N_2O emissions as detailed above, but uncertainty in production practices is also important. For the studies modelled in this thesis, these production uncertainties were derived from activity data collated as part of the FeedPrint project (Vellinga et al., 2013); the authors acknowledge that data limitations mean that in many cases, uncertainty in production practices is high. Lack of data on international imports and exports of livestock feed also means that it is difficult to ascertain the proportional origin of feeds produced outside the country of production; similarly, a generalised methodology to account for transport-based emissions is lacking. It is arguable that an emphasis on national-level reporting has contributed to this gap in the data; filling it would go some way towards improving the ability of LCA approaches and farm-level tools to holistically account for emissions from fed rations comprised of multiple imported components. The activity data collated as part of the FeedPrint project represents an excellent start in this respect, but developers of farm-level tools would undoubtedly benefit from research aimed at a) refining where possible uncertainties in activity data for crop production, and b) providing both flexibility and consensus on definition of system boundaries, particularly in contentious areas such as land use and land use change (LULUC).

Finally, the digestibility of the fed and grazed ration was found to be an important driver of uncertainty in emissions. This component affects primarily the CH_4 emissions from enteric fermentation, though also impacts production of manure, and hence manure-based CH_4 and N_2O emissions are also impacted by this parameter. Refinement of the methodology used to predict this parameter could take two forms; where systems are pasture based, refinement of modelling approach (as discussed in section 8.5) used to estimate this variable would serve to substantially reduce uncertainty in the overall beef estimate.

Further disaggregation and improvement of the data presented in the Feedipedia resource (INRA, 2012) would be the simplest way to further reduce uncertainty in the fed ration. Real-world variability exists in the DE% for any given crop, and this is characterised by estimated uncertainty in the data presented in the resource; as such, further disaggregation of this data would likely be necessary to reduce uncertainty. This would not necessarily increase data input burden, and could, for example, take the form of geographical distinction between cultivation regions, or distinction between cultivars in the presentation of the data.

A separate observation worth briefly discussing is that uncertainty combined additively reduces uncertainty in the whole (Röös & Nylinder, 2013); as such, rations comprised of a range of feeds are likely to have lower uncertainty than those comprised of one or two. In that the uncertainty is representative of real-world variation, this is likely to translate into practice; meaning combination of ration constituents will reduce uncertainty/variability in the nutritional quality of the cattle diet.

The majority of opportunities for methodological refinement presented in this section are the preserve of institutions, rather than individual researchers; the IPCC methodology, for example, is the result of an international collaboration. As such, this section serves to highlight areas for methodological development which were beyond the scope of this thesis to address, and would likely require considerable collaborative effort to achieve. Nonetheless, given the important and growing role of farm-level modelling approaches in agricultural GHG mitigation, it is expedient to define priorities for development of the underlying methodologies from the perspective of a farm-level modeller.

8.7.2. Opportunities for refinement of estimates of digestibility in farm-level models, LCA studies and national-level inventories

The analyses conducted throughout this thesis (chapters three – seven) make the most thorough attempt of which the author is aware to empirically model the nutritional quality of livestock rations as inputs to the IPCC Tier 2 methodology. This section discusses the value of this approach in respect of farm-level tools, LCA studies and national-level GHG inventories, and considers the opportunities for uptake of this approach beyond the AgRE Calc model.

The modelling approach (chapters five and six) and uncertainty study (chapter seven) undertaken in this thesis represents a novel empirical approach to estimate the sensitivity of beef production emissions to real-world uncertainty in the nutritional value of grazing land. Synthesis and uncertainty assessment of the impact of fed ration digestibility (chapter three) is also a first for this thesis. In treating grazing and fed ration digestibility separately, this thesis is more detailed than some assessments (e.g. Beauchemin et al., 2010; Dudley et al., 2014; Cardoso et al., 2016); most likely for reasons of data deficiency, such assessments specify dietary digestibility as a single value. This limits the extent to which the calculated footprint can be interrogated, and may, if the value represents a temporal generalisation, lead to inaccuracies in the estimate given the non-linearity of enteric methane response (see section 3.1). Finally, this thesis highlights the sensitivity of beef emissions intensity of production to the digestibility of the fed and grazed ration (chapter seven), supporting and expanding on the national-level findings of Milne et al. (2014).

Relatively few stochastic modelling assessments exist where this parameter is assessed. In previous LCA uncertainty assessments the authors have typically followed a different approach which utilises broader parameters, eclipsing the requirement for a specific estimate of digestibility (e.g. Gibbons et al., 2006; Dudley et al., 2014). National-level inventory uncertainty assessments (Monni et al., 2007; Karimi-Zindashty et al., 2012; Milne et al., 2014) have included this factor as a Monte Carlo variable, though have tended to utilise standard estimates, based on expert opinion, to characterise the parameter and surrounding uncertainty. These estimates are typically old and may be substituted between studies; for example, the estimate of uncertainty in digestible energy of cattle rations utilised by Milne et al. (2014) for the United Kingdom was taken directly from Monni et al. (2007), who utilised it in an assessment of the Finnish national inventory. These authors in turn took it from Pipatti (1997), an unpublished report written in Finnish. As such, these parameters risk becoming obsolete, both in terms of changing practice over time and application in different world regions. Even if this is not the case, future authors have little ability to critically appraise such an obscurely-derived parameter, so its validity becomes difficult to ascertain with confidence. Given the sensitivity of modelled ruminant livestock emissions to this value, it is desirable to quantify it as accurately and systematically as possible.

Resources such as Feedipedia (INRA, 2012), in providing nutritional data on fed rations, represent an invaluable resource to developers of farm-level tools, as well as practitioners of livestock-based life cycle analyses and national-level GHG inventory assessments. This thesis serves provide a blueprint by which feed digestibility, and surrounding uncertainty, can be simply calculated *de novo* based on the available data without undue effort on the part of the practitioner. Farm-level tools such as AgRE Calc fully automate this process, meaning that use of outdated and potentially invalid estimates for this parameter can be avoided moving forward. Based on analyses performed here, there is also opportunity for the IPCC to collate and standardise the available data and methods for incorporation into the next iteration of the guidelines for national GHG reporting; this would serve to substantially increase confidence in results of assessments performed using the IPCC Tier 2 methodology.

8.7.3. Moving from 'what-is' to 'what-if': development of an empirical animal performance sub-model

Interconnectivity between model processes is a key component of developing predictive abilities. The IPCC (2006) guidelines, which form the core of most farm-level models, are designed for GHG reporting; in other words, they are designed to be largely descriptive. The development of predictive sub-models (such as the grassland model developed in chapters five and six of this thesis) serve to increase the connectivity of separate calculation segments, and allows the farm-level model to respond holistically to changes in input data. Where model processes exist in isolation from one another, hypothetical system changes must be empirically calibrated across all input categories. This requires either expert guidance or access to real-world data; neither are readily available, the former is susceptible to arbitrary bias, and the latter largely negates the value of a hypothetical test. Linking of model processes via predictive sub-models circumvents these issues, though heterogeneity between farm-level ecosystems, both in terms of management and environment, increases the challenge of developing such approaches. It is nonetheless a valuable goal given that optimisation approaches such as linear programming, as well as an ability to model many hypothetical GHG mitigation options, rely on this inter-connectedness.

A key limitation of the IPCC Tier 2 equations for livestock (Dong et al., 2006), in terms of their application in farm-level models, is the lack of link between estimations of GHG emissions, feed consumption/requirements, and livestock performance. It is perhaps unfair to term this a limitation, as it falls outside the intended application of the methodology. Nonetheless, a way of linking these disparate data processes would be of great benefit to developers and users of farm-level tools. This thesis provides an initial step in this direction through the developments of a) the grass digestibility model (chapters five and six) and b) the sub-model for prediction of digestibility and crude protein in the fed ration (chapter three). There are still improvements to be made in this respect, however.

For hypothetical beef system simulations developed in this thesis, the author took the partial approach of employing pre-defined diets, and refining them to the energy requirements of the livestock class, calculated as defined by Dong et al. (2006). These final calculated values were then sense-checked against expert-supplied estimates from SAC (2016). This is in effect a best-of-both-worlds approach; some flexibility is gained from the predictive ability of the methodology, and available expert opinion is employed to ensure that the approach is not applied outside sensible limitations. The GLEAM model (MacLeod et al., 2013) follows a similar approach in that the user inputs livestock rations as a percentage ratio, and the model employs IPCC Tier 2 level calculations (Dong et al., 2006) to estimate the energy requirements of the livestock, and to subsequently calculate the actual quantities fed. In this sense, the Tier 2 methodology is used to describe the modelled system and to ensure that there is no net energy created or removed from the system.

However, while the Dong et al. (2006) equations can be employed to balance the energy requirements of a hypothetical system, prediction of livestock performance response to changes in feed quantity or quality is more difficult. A number of mathematical modelling approaches to this problem exist (Tedeschi et al., 2005), but so far the adoption of these in farm-level models has been limited. Salmon (2017) working on a modelled dairy system in sub-Saharan Africa, made an attempt to do this using this methodology. The author found that the approach was sufficient to make a mathematical prediction of the livestock response to dietary improvement, but noted that the nature of the methodology was a limiting factor in the approach. Essentially, the equations are designed to be one-way (predicting energy requirements from performance data), and reversing the direction of this calculation (predicting performance, i.e. growth rate, fecundity, milk production, etc. from energy requirements) requires considerable arbitration on the part of the researcher.

If models seek to move beyond footprinting reported activity data, animal performance considerations become a crucial aspect of the carbon footprint, and a key component of dietary trade-offs which form the basis of many GHG mitigation strategies (Beauchemin et al., 2008; Del Prado et al., 2013). A sub-model which could link basic aspects of animal performance response would be a valuable tool in the hands of researchers, policy makers, and agricultural consultants. This represents a challenging task; as well as the independent variables of feed quality and composition, a number of confounding variables would have to be addressed. For example, as noted by Salmon (2017), performance response is likely to depend heavily on animal breed and genetics, so capturing this would be a crucial aspect of methodological development. Despite these challenges, a wide body of research exists on the subject of modelling and quantifying cattle growth and performance (e.g. Oltjen et al., 1986; Arnold & Bennett, 1991; Hoch & Agabriel, 2004; Gomes et al., 2012). A priority for farm-level GHG model development should be reconciliation of this body of knowledge with the input data and resource restraints associated with farm-level modelling approaches. Such an approach would, if uncertainties could be reduced to a manageable level, allow the farm-level model to respond to holistically to changes in animal diet, and would greatly aid the user's ability to assess diet-related mitigation GHG strategies.

8.8. Final summary

8.8.1. Summary for farm-level modellers and LCA practitioners

Farm-level greenhouse models are empirical, broad-scope tools – as such, their development requires the combination and adaptation of a wide range of methodologies. Chapter two of this thesis (Sykes et al., 2017) serves to highlight the different ways in which this can be approached, and the impacts this can have on results calculated by ostensibly similar tools. The study also demonstrated the importance of documentation of tool methodology for transparency; where tools are sought for use in policy, this is especially important (Hall et al., 2010; CSA Wales, 2017). Development and documentation of a tool within the peer-review system may well represent the best way to ensure this level of transparency.

Tool developers should also be aware that complexity of models does not necessarily translate to accuracy (Gibbons et al., 2006; Essery et al., 2013), and that a high data input burden may largely negate the intended role of the tool (Hillier et al., 2011). Simplistic activity data, of the type available to farmers (or, at a larger scale, of the type collected in agricultural surveys and censuses) is typically sufficient to conduct a footprint using the methodologies employed by the farm-level tools sampled in chapter two. The role of tool developers is to effectively take this input as fixed, and to endeavour to gain the most value from it. This thesis effectively represents an exploration of this school of thought, and a number of the developments made to the AgRE Calc model are designed to increase flexibility and accuracy without increasing the burden of data input.

In furthering the development of farm-level models and LCA studies to this end, this thesis provides a number of resources which should enable developers and practitioners to advance in this respect. These include blueprints for a more detailed and flexible approach to the estimation of ration quality in ruminant livestock, for the estimation of grazing quality based on simple input parameters, and for conducting Monte Carlo uncertainty and sensitivity analyses for modelled cattle production systems.

Chapter seven highlights the importance of the latter development; epistemic uncertainty in farm-level GHG modelling exercises is high, and may vary considerably where different system types are compared (e.g. extensive vs. intensive). As such, it is a pertinent consideration in any comparison, and including a Monte Carlo simulation in the methodology may allow for a statistically supportable comparison to be made between systems. In addition to enabling estimates of epistemic uncertainty to be made (as was done in chapter seven) such an approach may serve to simulate or substitute for the variability between individuals and time periods highlighted in chapter four. In other cases, it may avoid the requirement for the researcher to cleave to a particular system type when in fact a range is typical, such as the simulation of parent systems in chapter four. This may mitigate or avoid arbitrary bias in subsequent calculation results. The literature shows that the majority of livestock footprinting studies which include Monte Carlo simulation (e.g. Gibbons et al., 2006; Karimi-Zindashty et al., 2012; Milne et al., 2014; Dudley et al., 2014) do so as the 'main theme' of the study; this thesis argues that the inclusion of a Monte Carlo estimate of uncertainty to provide context should be much more standard practice in this field. For studies following a holistic approach and utilising IPCC (2006) Tier 2 level methodologies for livestock, this thesis provides a compiled set of uncertainties and associated probability density functions (see appendix section A.2).

For the advancement of farm-level modelling, a number of areas representing 'low-hanging fruit' were identified by this thesis. These were discussed in detail in section 8.7, and developers of farm-level tools should be aware of these in terms of identifying which areas will yield the greatest returns in terms of time invested. A key component of this would be the integration of livestock performance models into farm-level GHG tools; achieving this would greatly increase the power of farm level tools in terms of modelling the 'what-if' scenarios which are crucial to mitigation strategy.

8.8.2 Summary for tool users and policy makers

Farm-level GHG models are powerful decision-support tools for aiding in consultancy and policy definition. The bottom-up approach which they facilitate is data-intensive, but necessary in a heterogeneous industry such as agriculture (Moran et al., 2011). However, there are a number of hurdles to overcome to enable their potential in policy definition to be reached.

Chapter two of this thesis (published as Sykes et al., 2017) highlighted the differences in results produced by a sample of publicly available farm-level tools from common input datasets. The publication also made some steps towards addressing the issues of transparency which up until this point has hindered the uptake of farm-level tools for policy guidance (e.g. Hall et al., 2010). The study provides a reference point for tool selection by policy makers, as exemplified by the consideration of AgRE Calc and the Sykes et al. (2017) paper in the CSA Wales (2017) project (H. Taft, pers. comm.), which seeks to develop or recommend a farm-level tool for use in policy definition by the Welsh assembly government.

Having selected an appropriate model, it is important to be aware of the impacts of input data quality and assumptions on the validity of the model output. Ideally, researchers utilising the model should make clear, either qualitatively or quantitatively, the level of confidence in each aspect of the model input and output; nonetheless, it is important that the end-user of these assessments has a high level of awareness of the implications of this. Data analysed in chapter four demonstrated the impacts of real-world ration and performance differences on the emissions intensity of beef finishing, and chapters five and six were developed in response to the observation of model sensitivity to parameters relating to grazing quality, and chapter seven further demonstrated the impacts of epistemic uncertainty in input parameters such as dietary digestibility, crude protein content, and embedded emissions in imported feed. End-users of tool output should be aware of the impact of these parameters, and should demand corresponding quantification of confidence levels by researchers. In general, an uncertainty analysis should go hand-in-hand with any quantitative GHG modelling exercise, and policy makers should be diligent in demanding and appraising this.

The LCA literature provides a variety of frames of reference for considering intensification of beef production systems (e.g. Subak, 1999; Casey & Holden, 2006; Hyslop, 2008; Pelletier et al., 2010; Cardoso et al., 2016). Frequently, the message of these studies favours a move towards intensifying production strategies. This thesis (chapter four) took the opportunity to utilise available high-quality experimental data to provide an in-depth analysis of this question, and found that, whilst improving the quality of cattle rations is a valid mitigation strategy, this may be achievable with lower overall impact by improving and supplementing a pasture-based system, rather than by following an intensive feedlot approach. In considering this issue, policy makers should be aware of displacing emissions abroad, through importation of concentrate feedstuffs; these emissions must be accounted for, and emissions from geographically diverse production systems are hard to quantify. Policy makers should also be aware of the potential for a move from extensive to intensive systems to substitute grazing land (unsuitable for the production of human-edible foodstuffs) for arable cropping land. The latter is likely to come under increasing pressure as the global population increases.

The carbon dioxide equivalent unit (CO_2-eq; based on Global Warming Potential metric) makes a convenient medium for the comparison of different emissions types, but tool users and especially policy makers should remain aware of its limitations. This is especially pertinent in the case of livestock agriculture, where different production strategies can effectively substitute one for another; a pertinent example is in the intensification of beef production, where enteric CH_4 is substituted for N_2O from arable cropping. The implications of this swap go far beyond the one-dimensional equivalence of the GWP metric, and policy makers should be aware of the qualitative differences involved. In general, there is a tendency for assessments of this type to attempt to distil results into a single metric, and this may not always represent a rounded approach. This is further compounded by the fact that many carbon footprinting tools do not account for other environmental burdens (e.g. eutrophication, acidification), and users should be cognisant of the potential impacts of modelled measures on these unquantified factors.

8.8.3. Summary for IPCC

The IPCC (2006) methodologies are not designed for farm-level GHG accounting, but rather for national-level assessments. Nonetheless, they feature prominently in all of the tools sampled in chapter two of this thesis (Sykes et al., 2017). Simultaneously, policy makers are struggling to deal with the heterogeneity of agricultural systems in terms of emissions abatement, and top-down approaches (guided by the IPCC methodologies and national-level GHG accounting) which work well in more centralised industries (e.g. power generation) are less effective in agriculture (Moran et al., 2011). As a result, policy makers are turning to bottom-up approaches (for which farm-level GHG models are effectively a facilitator) in order to find the best approaches to mitigate GHGs from agriculture (e.g. Hall et al., 2010; CSA Wales, 2017; Macleod et al., 2017). These observations suggest that it would be advantageous if the IPCC recognised the potential role of farm-level GHG tools in facilitating mitigation policy, and the use to which the IPCC (2006) guidelines are being put in this respect. If the next iteration of these guidelines were to include some guidance on the application and adaptation of these methods at farm level, it would go some way towards standardising the methods utilised by tool developers, which can be somewhat variable (e.g. chapter two; Sykes et al., 2017). In particular, issues of allocation of emissions are more pertinent at small scales, and this factor may go some way towards explaining the variability in results of tools sampled in chapter two. Likewise, farm-level studies follow a holistic approach which national-level inventories do not; as such, inclusion of upstream emissions is of greater importance. Guidance on allocation of emissions, and environmental burdens associated with production of imported products (e.g. feed and agrochemicals) are increasingly available (e.g. Agri-footprint, Durlinger et al., 2014); as such, new iterations of the guidelines are in a position to draw on such resources and to provide guidance on holistic, small-scale footprinting. This would serve to greatly improve the consistency with which farm-level models estimate emissions relating to these factors.

An area where issues of scale are especially pertinent is in consideration of uncertainties; the IPCC (2006) guidelines provide estimates of uncertainty in most mathematical parameters, but do not provide background to these or guidance as to the scale at which these parameters should be applied. As additive combination of uncertainties serves to decrease overall uncertainty (Röös & Nylinder, 2013), this is an important consideration.

Finally, chapter seven of this thesis identified a number of Tier 2 coefficients where uncertainty greatly affects the estimate for emissions from ruminant livestock production. The impacts of these are likely to be important at national level as well; reports from national-level uncertainty studies (Karimi-Zindashty et al., 2012; Milne et al., 2014) corroborate this finding. As such, refinement of these coefficients in such a way that uncertainty was reduced would go a long way towards improving the confidence with which emissions estimates from livestock, both at farm- and national-level, can be made. Section 8.7 considers some of the approaches which could be taken to this end, and the challenges associated with this.

8.8.4. Materials and resources provided by this thesis

In line with the development framework identified in the introduction (section 1.4), this thesis has generated a number of resources which may be of value to developers of farm-level GHG modelling tools, and practitioners of livestock LCA studies. These are summarised here:

1. Framework for estimation of livestock dietary digestibility based on individual fed ration components (section 3.1; appendix section A.1)
2. Framework for calculation of grazing digestibility based on sward management; estimates of grazing digestibility based on variety of management practices, with associated uncertainty calculated via Monte Carlo simulation (chapters five, six; table 5.8)
3. Collation of literature estimates of digestibility for individual species and mixed swards (appendix section A.5)
4. Framework for stochastic analysis of epistemic uncertainty in holistic GHG models for livestock production systems (section 3.4)
5. Collated epistemic uncertainty parameters for any farm-level modelling activity (appendix section A.2)

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Appendix

A.1. Base data for diet characterisation in AgRE Calc

Chapter three of this thesis described the process by which parameters describing the nutritional characteristics of cattle rations were incorporated into the AgRE Calc model. This allowed the parameters for equations defining the production of enteric CH_4, manure CH_4 and manure N_2O to be modified to reflect the exact ration of individual animal classes. This section presents the data which was collated to form the basis of these calculations (Tables A.1 and A.2).

Table A.1. Nutritional data for homegrown livestock feeds as utilised in AgRE Calc. Data sourced from Feedipedia online resource (INRA, 2012).

Homegrown Feeds	Dry matter **% as fed**	Crude protein **% DM**	Gross energy **MJ kg DM^{-1}**	DE, ruminants **% gross energy**
Silage & graze	31.7 ± 2.5	8.8 ± 0.9	17.7 ± 0.7	60.8 ± 2.4
Hay & graze	88.6 ± 2.0	10.1 ± 1.3	17.9 ± 0.3	58.1 ± 4.7
Kale/turnips/swedes/etc.	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Fodder beet	16.3 ± 2.2	6.7 ± 1.1	16.7 ± 0.4	84.6 ± 1.6
Wholecrop cereals	27.2 ± 3.3	10.2 ± 2.0	17.8 ± 0.3	64.1 ± 5.2
Forage maize	28.2 ± 1.3	7.3 ± 0.9	19.0 ± 0.1	68.6 ± 2.3
Legume forages	18.4 ± 3.7	22.8 ± 2.2	18.2 ± 0.6	71.4 ± 8.8
Cereal/legume straw	91.0 ± 1.3	4.2 ± 0.7	18.5 ± 0.6	45.2 ± 3.7
Feed wheat	87.0 ± 1.3	12.6 ± 1.3	18.2 ± 0.2	85.7 ± 2.7
Feed winter barley	87.1 ± 1.3	11.8 ± 1.1	18.4 ± 0.1	80.7 ± 2.1
Feed spring barley	87.1 ± 1.3	11.8 ± 1.1	18.4 ± 0.1	80.7 ± 2.1
Winter oats	87.9 ± 1.4	11.0 ± 1.4	19.5 ± 0.2	75.5 ± 3.5
Spring oats	87.9 ± 1.4	11.0 ± 1.4	19.5 ± 0.2	75.5 ± 3.5
Minor cereals	86.9 ± 0.8	11.0 ± 0.8	18.1 ± 0.1	85.8 ± 7.0
Oilseed rape	90.9 ± 1.7	37.6 ± 2.2	20.3 ± 0.8	78.5 ± 6.4
Field beans	86.6 ± 1.4	29.0 ± 1.8	18.7 ± 0.2	89.8 ± 3.0
Field peas	86.5 ± 1.2	23.9 ± 1.4	18.3 ± 0.1	90.3 ± 1.7
Feed potatoes	20.2 ± 1.3	10.8 ± 0.7	16.9 ± 0.2	87.1 ± 1.6
Sugar beet	18.8 ± 4.2	7.8 ± 1.5	16.9 ± 0.0	87.6 ± 7.1
Swedes / turnips	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Carrots	10.7 ± 1.5	9.1 ± 3.2	17.1 ± 0.0	83.1 ± 6.8
Other root veg	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Processing peas	86.5 ± 1.2	23.9 ± 1.4	18.3 ± 0.1	90.3 ± 1.7
Processing beans	86.6 ± 1.4	29.0 ± 1.8	18.7 ± 0.2	89.8 ± 3.0
Other legume veg	86.6 ± 0.9	26.5 ± 1.1	18.5 ± 0.1	90.1 ± 1.7
Cabbages	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Cauliflower	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Calabrese	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Brussel sprouts	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6
Other brassica veg.	16.6 ± 1.5	9.2 ± 1.2	17.0 ± 0.2	85.9 ± 1.6

Table A.2. Nutritional data for purchased livestock feeds as utilised in AgRE Calc. Data sourced from Feedipedia online resource (INRA, 2012).

Imported Feeds	Dry matter % as fed	Crude protein % DM	Gross energy MJ kg DM^{-1}	DE, ruminants % gross energy
Hay	88.6 ± 2.0	10.1 ± 1.3	17.9 ± 0.3	58.1 ± 4.7
Grass silage	31.7 ± 2.5	8.8 ± 0.9	17.7 ± 0.7	60.8 ± 2.4
Wholecrop cereals	27.2 ± 3.3	10.2 ± 2.0	17.8 ± 0.3	64.1 ± 5.2
Maize silage	28.2 ± 1.3	7.3 ± 0.9	19.0 ± 0.1	68.6 ± 2.3
Straw	91.0 ± 1.3	4.2 ± 0.7	18.5 ± 0.6	45.2 ± 3.7
Clover silage	27.7 ± 6.4	18.9 ± 2.3	18.9 ± 0.5	64.7 ± 5.7
Fodder beet	16.3 ± 2.2	6.7 ± 1.1	16.7 ± 0.4	84.6 ± 1.6
Lucerne	19.9 ± 3.1	20.6 ± 3.4	18.1 ± 1.0	65.5 ± 8.8
Brewers grains	91.0 ± 2.5	25.8 ± 3.1	19.7 ± 1.8	63.2 ± 4.7
Citrus pulp	89.6 ± 1.2	7.0 ± 0.6	17.3 ± 0.3	83.9 ± 3.4
Wheat (grain)	87.0 ± 1.3	12.6 ± 1.3	18.2 ± 0.2	85.7 ± 2.7
Barley (grain)	87.1 ± 1.3	11.8 ± 1.1	18.4 ± 0.1	80.7 ± 2.1
Oats (grain)	87.9 ± 1.4	11.0 ± 1.4	19.5 ± 0.2	75.5 ± 3.5
Potatoes (brock)	20.2 ± 1.3	10.8 ± 0.7	16.9 ± 0.2	87.1 ± 1.6
Potatoes (ware)	20.2 ± 1.3	10.8 ± 0.7	16.9 ± 0.2	87.1 ± 1.6
Soya meal	87.9 ± 0.9	51.8 ± 1.8	19.7 ± 0.3	92.2 ± 7.5
Rape Meal	90.9 ± 1.2	37.6 ± 1.5	20.3 ± 0.6	78.5 ± 6.4
Distillers Pellets	90.7 ± 1.9	27.8 ± 2.1	21.3 ± 0.6	70.9 ± 4.7
Maize gluten	88.3 ± 1.5	21.7 ± 1.5	18.8 ± 0.3	80.4 ± 1.5
Molasses	73.0 ± 1.8	5.5 ± 1.4	14.7 ± 0.6	76.6 ± 6.2
Beef and calf nuts	86.2 ± 0.9	18.2 ± 0.8	18.4 ± 0.1	79.2 ± 1.7
Ewe and lamb nuts	80.0 ± 1.0	20.2 ± 0.8	18.1 ± 0.1	81.5 ± 2.1
Dairy and calf nuts	83.7 ± 0.7	22.3 ± 0.7	18.4 ± 0.1	81.2 ± 1.7
Milk powder	94.5 ± 4.7	35.0 ± 1.8	16.1 ± 0.8	83.7 ± 4.2
Minerals	100.0 ± 0.0	n/a	n/a	n/a
Field beans	86.6 ± 1.4	29.0 ± 1.8	18.7 ± 0.2	89.8 ± 3.0
Waste vegetables	23.2 ± 1.2	15.9 ± 1.3	17.3 ± 0.1	83.4 ± 1.7
Sugar beet pulp	89.2 ± 1.3	9.3 ± 0.9	17.0 ± 0.5	80.2 ± 4.3

A.2. Record of Monte Carlo parameters defined during AgRE Calc development

This section contains a record of the parameters collated defined to render the AgRE Calc model capable of performing Monte Carlo uncertainty and sensitivity analyses, as described in section 3.4 of this thesis. A subset of the parameters defined here were utilised in the analyses conducted in chapter seven of this thesis. The equations for the four probability distributions utilised are presented below (equations A.1 – A.4), and the parameterisation of these in the AgRE Calc model is described in table A.3.

Equation A.1. Probability density function for the normal distribution (Casella & Berger, 2001).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \boldsymbol{e}^{-\frac{(\boldsymbol{x}-\boldsymbol{\mu})^2}{2\boldsymbol{\sigma}^2}}$$

Where:
x = variable estimate
μ = sample mean
σ = sample standard deviation
π ≈ 3.14159
e ≈ 2.71828

Equation A.2. Probability density function for the lognormal distribution (Aitchison & Brown, 1957; Casella & Berger, 2001).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}$$

Where:
x = variable estimate
μ = sample mean
σ = sample standard deviation
π ≈ 3.14159
e ≈ 2.71828

Equation A.3. Probability density function for the Beta PERT distribution (Clark, 1962).

$$f(x) = \frac{(x-a)^{\boldsymbol{\alpha-1}}(c-x)^{\boldsymbol{\beta-1}}}{B(\alpha,\beta)(c-a)^{\alpha+\beta+1}}$$

Where:
x = variable estimate
a = minimum estimate for x
b = modal estimate for x
c = maximum estimate for x

$$\alpha = \frac{4b + c + 5a}{c - a}$$

$$\beta = \frac{5c - a - 4}{c - a}$$

$$B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

Equation A.4. Probability density function for the uniform distribution (Casella & Berger, 2001).

$$f(x) = \begin{cases} \dfrac{1}{b-a} & x \in [a,b] \\ 0 & \text{otherwise} \end{cases}$$

Where:
x = variable estimate
a = minimum estimate for x
b = maximum estimate for x

Table A.3. Collated probability density function parameters utilised in the AgRE Calc model, presented with source and categorised according to utilisation in the model. Bold, italicised entries represent those which were utilised in the analyses performed in chapter seven.

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
Livestock emissions	***Cfi: lactating cow***	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.386***	***0.059***	-	-
	Cfi: non lactating cow	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.322***	***0.049***	-	-
	Cfi: bulls	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.370***	***0.056***	-	-
	Ca: Housed	Dong et al. (2006)	Monni et al. (2007)	Normal	0.000	0.000	-	-
	Ca: Field	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.170***	***0.026***	-	-
	Ca: Hill	Dong et al. (2006)	Monni et al. (2007)	Normal	0.360	0.055	-	-
	Cpregnancy	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.100***	***0.005***	-	-
	C: Females	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.800***	***0.122***	-	-
	C: Steers	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***1.000***	***0.153***	-	-
	C: Bulls	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***1.200***	***0.184***	-	-
	Suckler cow milk BF%	***SAC (2016)***	***Milne et al. (2014)***	***Normal***	***4.300***	***0.110***	-	-
	Ym: other cattle	***Dong et al. (2006)***	***Dong et al. (2006)***	***Normal***	***6.500***	***0.521***	***5.500***	***7.500***
	Ym: feedlot cattle	Dong et al. (2006)	Dong et al. (2006)	Normal	3.000	0.521	2.000	4.000
	B0: Other cattle	***Dong et al. (2006)***	***Dong et al. (2006)***	***Normal***	***0.180***	***0.013***	-	-
	MCF @ 10oC: liquid slurry	Dong et al. (2006)	Monni et al. (2007)	Normal	0.170	0.026	-	-
	MCF @ 10oC: solid storage	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.020***	***0.003***	-	-
	MCF @ 10oC: pasture/range/paddo ck	***Dong et al. (2006)***	***Monni et al. (2007)***	***Normal***	***0.010***	***0.002***	-	-
	MCF @ 10oC: pit storage	Dong et al. (2006)	Monni et al. (2007)	Normal	0.170	0.026	-	-
	MCF @ 10oC: deep bedding	Dong et al. (2006)	Monni et al. (2007)	Normal	0.170	0.026	-	-
	EF3: pasture range and paddock	***Dong et al. (2006)***	***Milne et al. (2014)***	***Lognormal***	***-3.912***	***0.548***	-	-
	EF3: solid storage and drylot	***Dong et al. (2006)***	***Milne et al. (2014)***	***Lognormal***	***-5.298***	***0.354***	-	-
	EF3: pit storage	Dong et al. (2006)	Milne et al. (2014)	Lognormal	-6.215	0.354	-	-
	EF3: deep bedding	Dong et al. (2006)	Milne et al. (2014)	Lognormal	-4.605	0.354	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	EF3: poultry with or without litter	Dong et al. (2006)	Milne et al. (2014)	Lognormal	-6.908	0.354	-	-
	Volatilisation: manure deposition (FracGASM)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.200***	***-***	***0.050***	***0.500***
	Volatilisation: manure liquid/slurry	Dong et al. (2006)	Dong et al. (2006)	Beta PERT	0.400	-	0.150	0.450
	Volatilisation: manure solid storage	***Dong et al. (2006)***	***Dong et al. (2006)***	***Beta PERT***	***0.450***	***-***	***0.100***	***0.650***
	Volatilisation: manure pit storage	Dong et al. (2006)	Dong et al. (2006)	Beta PERT	0.280	-	0.100	0.400
	Volatilisation: manure deep bedding	Dong et al. (2006)	Dong et al. (2006)	Beta PERT	0.300	-	0.200	0.400
	Farm manure: Frac indirect emissions from volatilised N (EF4)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.605***	***0.821***	***0.002***	***0.050***
	Leaching: manure deposition (FracLEACH)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.300***	***-***	***0.100***	***0.800***
	Leaching: manure solid storage	***Dong et al. (2006)***	***Dong et al. (2006)***	***Beta PERT***	***0.050***	***-***	***0.020***	***0.100***
	Leaching: manure deep bedding	Dong et al. (2006)	Dong et al. (2006)	Beta PERT	0.100	-	0.050	0.200
	Farm manure: Frac indirect emissions from leaching (EF5)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.893***	***0.998***	***0.0005***	***0.025***
	Farm manure spread: Frac direct N emissions to soil (EF1)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.605***	***0.587***	***0.003***	***0.030***
	Volatilisation: Farm manure spread (FracGASM)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.200***	***-***	***0.050***	***0.500***
	Leaching: Farm manure spread (FracLEACH)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.300***	***-***	***0.100***	***0.800***
Emissions from land and crops	Crop residues: Grains [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.090	0.011	-	-
	Crop residues: Beans [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.130	0.107	-	-
	Crop residues: Tubers [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.100	0.035	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Crop residues: Root crops, other [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.070	0.102	-	-
	Crop residues: N-fixing forages [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.300	0.075	-	-
	Crop residues: Non-N-fixing forages [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.300	0.075	-	-
	Crop residues: Perennial grasses [Slope]	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Normal***	***0.300***	***0.075***	***-***	***-***
	Crop residues: Grass-clover mixtures [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.300	0.075	-	-
	Crop residues: Maize [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.030	0.015	-	-
	Crop residues: Wheat [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.510	0.023	-	-
	Crop residues: Winter wheat [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.610	0.024	-	-
	Crop residues: Spring wheat [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.290	0.032	-	-
	Crop residues: Rice [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.950	0.090	-	-
	Crop residues: Barley [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.980	0.039	-	-
	Crop residues: Oats [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.910	0.023	-	-
	Crop residues: Millet [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.430	0.129	-	-
	Crop residues: Sorghum [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.880	0.057	-	-
	Crop residues: Rye [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.090	0.273	-	-
	Crop residues: Soyabean [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.930	0.144	-	-
	Crop residues: Dry bean [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.360	0.180	-	-
	Crop residues: Potato [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.100	0.035	-	-
	Crop residues: Peanut [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.070	0.102	-	-
	Crop residues: Alfalfa [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.290	0.045	-	-
	Crop residues: Non-legume hay [Slope]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.180	0.045	-	-
	Crop residues: Grains [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.880	0.026	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Crop residues: Beans [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.850	0.238	-	-
	Crop residues: Tubers [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.060	0.371	-	-
	Crop residues: Root crops, other [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.540	0.316	-	-
	Crop residues: N-fixing forages [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Non-N-fixing forages [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Perennial grasses [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Grass-clover mixtures [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Maize [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.610	0.058	-	-
	Crop residues: Wheat [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.520	0.044	-	-
	Crop residues: Winter wheat [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.400	0.050	-	-
	Crop residues: Spring wheat [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.750	0.098	-	-
	Crop residues: Rice [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	2.460	0.504	-	-
	Crop residues: Barley [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.590	0.121	-	-
	Crop residues: Oats [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.890	0.036	-	-
	Crop residues: Millet [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.140	0.216	-	-
	Crop residues: Sorghum [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.330	0.180	-	-
	Crop residues: Rye [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.880	0.220	-	-
	Crop residues: Soyabean [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.350	0.331	-	-
	Crop residues: Dry bean [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.680	0.160	-	-
	Crop residues: Potato [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.060	0.371	-	-
	Crop residues: Peanut [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	1.540	0.316	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Crop residues: Alfalfa [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Non-legume hay [Intercept]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Grains [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.220	0.018	-	-
	Crop residues: Beans [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.190	0.043	-	-
	Crop residues: Tubers [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.200	0.050	-	-
	Crop residues: Root crops, other [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.200	0.050	-	-
	Crop residues: N-fixing forages [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.400	0.100	-	-
	Crop residues: Non-N-fixing forages [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.540	0.135	-	-
	Crop residues: Perennial grasses [RBG-BIO]	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Normal***	***0.800***	***0.200***	-	-
	Crop residues: Grass-clover mixtures [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.800	0.200	-	-
	Crop residues: Maize [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.220	0.029	-	-
	Crop residues: Wheat [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.240	0.038	-	-
	Crop residues: Winter wheat [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.230	0.047	-	-
	Crop residues: Spring wheat [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.280	0.036	-	-
	Crop residues: Rice [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.160	0.028	-	-
	Crop residues: Barley [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.220	0.036	-	-
	Crop residues: Oats [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.250	0.150	-	-
	Crop residues: Millet [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Sorghum [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Rye [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Crop residues: Soyabean [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.190	0.043	-	-
	Crop residues: Dry bean [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Potato [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.200	0.050	-	-
	Crop residues: Peanut [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.000	0.000	-	-
	Crop residues: Alfalfa [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.400	0.100	-	-
	Crop residues: Non-legume hay [RBG-BIO]	de Klein et al. (2006)	de Klein et al. (2006)	Normal	0.540	0.135	-	-
	Crop residues: Frac direct N emissions to soil (EF1)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.605***	***0.587***	***0.003***	***0.030***
	Leaching: Crop residues (FracLEACH)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.300***	***-***	***0.100***	***0.800***
	Crop residues: Frac indirect emissions from leaching (EF5)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.893***	***0.998***	***0.001***	***0.025***
	Imported manure spread: Frac direct N emissions to soil (EF1)	de Klein et al. (2006)	de Klein et al. (2006)	Lognormal	-4.605	0.587	0.003	0.030
	Volatilisation: Imported manure spread (FracGASM)	de Klein et al. (2006)	de Klein et al. (2006)	Beta PERT	0.200	-	0.050	0.500
	Leaching: Imported manure spread (FracLEACH)	de Klein et al. (2006)	de Klein et al. (2006)	Beta PERT	0.300	-	0.100	0.800
	Imported manure: Frac indirect emissions from volatilised N (EF4)	de Klein et al. (2006)	de Klein et al. (2006)	Lognormal	-4.605	0.821	0.002	0.050
	Imported manure: Frac indirect emissions from leaching (EF5)	de Klein et al. (2006)	de Klein et al. (2006)	Lognormal	-4.893	0.998	0.0005	0.025
	Fertiliser spread: Frac direct N emissions to soil (EF1)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.605***	***0.587***	***0.003***	***0.030***

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Volatilisation: Fertiliser spread (FracGASF)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.100***	***-***	***0.030***	***0.300***
	Leaching: Fertiliser spread (FracLEACH)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Beta PERT***	***0.300***	***-***	***0.100***	***0.800***
	Fertiliser: Frac indirect emissions from volatilised N (EF4)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.605***	***0.821***	***0.002***	***0.050***
	Fertiliser: Frac indirect emissions from leaching (EF5)	***de Klein et al. (2006)***	***de Klein et al. (2006)***	***Lognormal***	***-4.893***	***0.998***	***0.0005***	***0.025***
	Lime CO2-C EF	de Klein et al. (2006)	de Klein et al. (2006)	Beta PERT	0.125	-	0.0625	0.125
	Urea CO2-C EF	de Klein et al. (2006)	de Klein et al. (2006)	Beta PERT	0.200	-	0.1000	0.200
Emissions from fuels and electricity	Electricity EF [Albania] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.006982	-	0.00192	0.06439
	Electricity EF [Algeria] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.549201	-	0.54577	0.63187
	Electricity EF [Angola] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.390844	-	0.19092	0.43024
	Electricity EF [Argentina] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.397174	-	0.2581	0.39717
	Electricity EF [Armenia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.176518	-	0.09225	0.24302
	Electricity EF [Australia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.798902	-	0.7989	0.92875
	Electricity EF [Austria] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.164791	-	0.16323	0.23291
	Electricity EF [Azerbaijan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.493662	-	0.43106	0.64834
	Electricity EF [Bahrain] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.754719	-	0.6012	0.88305

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Bangladesh] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.575116	-	0.54555	0.60362
	Electricity EF [Belarus] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.425118	-	0.29215	0.44946
	Electricity EF [Belgium] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.212018	-	0.19572	0.28434
	Electricity EF [Benin] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.720699	-	0.60133	1.1011
	Electricity EF [Bolivia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.426278	-	0.25464	0.43332
	Electricity EF [Bosnia and Herzegovina] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.973813	-	0.72261	0.97676
	Electricity EF [Botswana] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	1.478836	-	1.31799	2.18971
	Electricity EF [Brazil] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.098174	-	0.06413	0.10335
	Electricity EF [Brunei Darussalam] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.722667	-	0.70281	0.81812
	Electricity EF [Bulgaria] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.531694	-	0.43068	0.59131
	Electricity EF [Cambodia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.52896	-	0.52896	1.96985
	Electricity EF [Cameroon] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.208595	-	0.01004	0.24268
	Electricity EF [Canada] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.150889	-	0.15089	0.2311

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Chile] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.482977	-	0.27351	0.48298
	Electricity EF [China (including Hong Kong)-IEA] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.734285	-	0.73429	0.80447
	Electricity EF [Colombia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.122768	-	0.10702	0.17574
	Electricity EF [Congo] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.22996	-	0.08181	0.26704
	Electricity EF [Costa Rica] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.054356	-	0.00746	0.07152
	Electricity EF [Côte d'Ivoire] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.490381	-	0.35609	0.49038
	Electricity EF [Croatia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.311063	-	0.23627	0.38487
	Electricity EF [Cuba] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.897256	-	0.56792	1.01444
	Electricity EF [Cyprus] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.726296	-	0.70467	0.83763
	Electricity EF [Czech Republic] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.55185	-	0.51425	0.59521
	Electricity EF [Dem. People's Republic of Korea] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.378048	-	0.37805	0.58359
	Electricity EF [Democratic Republic of Congo] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.002884	-	0.00053	0.0039
	Electricity EF [Denmark] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.257264	-	0.25726	0.36553

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Dominican Republic] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.555251	-	0.5552 5	0.7594 3
	Electricity EF [Ecuador] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.313021	-	0.2152 6	0.4546 7
	Electricity EF [Egypt] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.44376	-	0.3810 1	0.4740 3
	Electricity EF [El Salvador] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.238351	-	0.2202 2	0.3616
	Electricity EF [Eritrea] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.84934	-	0.6464 1	0.8504 9
	Electricity EF [Estonia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.911993	-	0.6518 1	1.0858 8
	Electricity EF [Ethiopia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.006635	-	0.0029 1	0.1185 3
	Electricity EF [Finland] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.13415	-	0.1341 5	0.2916 2
	Electricity EF [France] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.069254	-	0.0612 5	0.0932 1
	Electricity EF [FYR of Macedonia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.853219	-	0.6763 2	0.8532 2
	Electricity EF [Gabon] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.436126	-	0.2833 8	0.4361 3
	Electricity EF [Georgia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.117013	-	0.0687 4	0.2250 1
	Electricity EF [Germany] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.475408	-	0.4042 5	0.5076 8

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Ghana] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.249445	-	0.06555	0.35963
	Electricity EF [Gibraltar] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.748511	-	0.73952	0.77101
	Electricity EF [Greece] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.68461	-	0.68461	0.83121
	Electricity EF [Guatemala] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.254234	-	0.25423	0.48416
	Electricity EF [Haiti] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.591677	-	0.3006	0.59168
	Electricity EF [Honduras] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.363475	-	0.26656	0.45238
	Electricity EF [Hong Kong, China] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.757798	-	0.71182	0.79505
	Electricity EF [Hungary] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.314012	-	0.30206	0.42465
	Electricity EF [Iceland] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.000178	-	0.00018	0.00137
	Electricity EF [India] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.926098	-	0.85584	0.95426
	Electricity EF [Indonesia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.809188	-	0.65345	0.80919
	Electricity EF [Iraq] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.907319	-	0.68409	1.00284
	Electricity EF [Ireland] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.456584	-	0.42672	0.66821

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Islamic Republic of Iran] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.568679	-	0.52927	0.62996
	Electricity EF [Israel] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.766672	-	0.68723	0.8118
	Electricity EF [Italy] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.385041	-	0.38504	0.51086
	Electricity EF [Jamaica] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.642774	-	0.4001	0.82409
	Electricity EF [Japan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.550884	-	0.40059	0.55088
	Electricity EF [Jordan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.635616	-	0.57548	0.74021
	Electricity EF [Kazakhstan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.460875	-	0.40886	0.56965
	Electricity EF [Kenya] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.223178	-	0.14112	0.44488
	Electricity EF [Korea] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.540337	-	0.44933	0.54541
	Electricity EF [Kuwait] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.744971	-	0.72127	0.86961
	Electricity EF [Kyrgyzstan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.034787	-	0.03479	0.10592
	Electricity EF [Latvia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.091084	-	0.09108	0.19963
	Electricity EF [Lebanon] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.805641	-	0.59096	0.80564

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Libya] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.568603	-	0.5686	1.02236
	Electricity EF [Lithuania] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.271192	-	0.11115	0.33787
	Electricity EF [Luxembourg] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.340341	-	0.34034	0.51692
	Electricity EF [Malaysia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.671363	-	0.47591	0.72351
	Electricity EF [Malta] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.871526	-	0.81902	1.03378
	Electricity EF [Mexico] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.453445	-	0.43032	0.57095
	Electricity EF [Middle East] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.667338	-	0.66734	0.71431
	Electricity EF [Mongolia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.884103	-	0.52331	0.94662
	Electricity EF [Morocco] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.69663	-	0.63844	0.76561
	Electricity EF [Mozambique] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.001182	-	0.0004	0.00474
	Electricity EF [Myanmar] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.216206	-	0.19585	0.457
	Electricity EF [Namibia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.026996	-	0.00132	0.42386
	Electricity EF [Nepal] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.003814	-	0.00102	0.01229

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Netherlands] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.440697	-	0.37449	0.4407
	Electricity EF [Netherlands Antilles] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.706816	-	0.70654	0.71436
	Electricity EF [New Zealand] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.173282	-	0.1406	0.23357
	Electricity EF [Nicaragua] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.406625	-	0.40663	0.61367
	Electricity EF [Nigeria] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.403224	-	0.32617	0.43258
	Electricity EF [Norway] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.008057	-	0.00406	0.01729
	Electricity EF [Oman] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.602076	-	0.60208	0.88678
	Electricity EF [Other Africa] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.468881	-	0.36076	0.52717
	Electricity EF [Other Asia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.315232	-	0.25764	0.36176
	Electricity EF [Pakistan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.417622	-	0.37076	0.47945
	Electricity EF [Panama] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.32559	-	0.23107	0.39948
	Electricity EF [Peru] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.285562	-	0.12288	0.29737
	Electricity EF [Philippines] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.502374	-	0.43303	0.50237

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Poland] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.755835	-	0.6402	0.78135
	Electricity EF [Portugal] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.363959	-	0.25532	0.51196
	Electricity EF [Qatar] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.492949	-	0.48973	0.78172
	Electricity EF [Republic of Moldova] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.497125	-	0.4001	0.76719
	Electricity EF [Romania] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.480628	-	0.3958	0.49869
	Electricity EF [Russian Federation] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.428779	-	0.3174	0.43735
	Electricity EF [Saudi Arabia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.738216	-	0.72611	0.80538
	Electricity EF [Senegal] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.601722	-	0.52031	0.79915
	Electricity EF [Serbia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.759947	-	0.63584	0.82511
	Electricity EF [Singapore] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.472479	-	0.47248	0.76198
	Electricity EF [Slovak Republic] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.194386	-	0.19439	0.26669
	Electricity EF [Slovenia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.331476	-	0.31603	0.37149
	Electricity EF [South Africa] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.913527	-	0.81941	0.94774

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Spain] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.305355	-	0.23741	0.43402
	Electricity EF [Sri Lanka] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.542092	-	0.33528	0.54209
	Electricity EF [Sudan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.201957	-	0.16512	0.61204
	Electricity EF [Sweden] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.012358	-	0.01236	0.05939
	Electricity EF [Switzerland] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.028036	-	0.0273	0.04613
	Electricity EF [Syrian Arab Republic] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.582416	-	0.55885	0.65403
	Electricity EF [Tajikistan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.001281	-	0.00128	0.03761
	Electricity EF [Thailand] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.500424	-	0.50042	0.56701
	Electricity EF [Togo] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.171288	-	0.17129	1.4932
	Electricity EF [Trinidad and Tobago] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.676371	-	0.50575	0.76717
	Electricity EF [Tunisia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.459029	-	0.4555	0.58442
	Electricity EF [Turkey] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.459145	-	0.41938	0.54389
	Electricity EF [Turkmenistan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.986745	-	0.78945	0.98674

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Electricity EF [Ukraine] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.459976	-	0.3164 8	0.4599 8
	Electricity EF [United Arab Emirates] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.597276	-	0.5972 8	0.9132 2
	Electricity EF [United Kingdom] (kWh)	***GHG Protocol (2012)***	***GHG Protocol (2000-2012)***	***Beta PERT***	***0.47948***	***-***	***0.4406 7***	***0.5073 6***
	Electricity EF [United Republic of Tanzania] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.486806	-	0.0508 8	0.4868 1
	Electricity EF [United States] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.480686	-	0.4806 9	0.6168 1
	Electricity EF [Uruguay] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.273444	-	0.0018 9	0.3067 7
	Electricity EF [Uzbekistan] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.54611	-	0.4438 4	0.5588 2
	Electricity EF [Venezuela] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.265393	-	0.1911 8	0.2659 6
	Electricity EF [Vietnam] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.351215	-	0.3512 2	0.4480 3
	Electricity EF [Yemen] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.650475	-	0.6304 5	0.9301
	Electricity EF [Zambia] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.002647	-	0.0022 2	0.0069 6
	Electricity EF [Zimbabwe] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.365122	-	0.3577 1	0.8482 7
	Electricity EF [Country Not Specified] (kWh)	GHG Protocol (2012)	GHG Protocol (2000-2012)	Beta PERT	0.45353	-	0.0001 8	2.1897 1

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Diesel - red: EF	***DEFRA/DECC (2015)***	***DEFRA/DECC (2012-2015)***	***Beta PERT***	***3.165***	***0.039***	***3.165***	***3.248***
	Diesel (derv) - white: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	3.165	0.039	3.165	3.248
	Petrol: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	2.656	0.029	2.656	2.717
	Kerosene / Burning oil: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	3.056	0.006	3.056	3.071
	LPG: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	1.699	0.019	1.680	1.724
	Mains gas: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	0.209	0.003	0.204	0.212
	Coal: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	3.487	0.109	3.258	3.487
	Renewable heat from wood logs/chips used: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	0.013	0.001	0.012	0.013
	Renewable heat from wood pellets used: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	0.013	0.001	0.012	0.013
	Renewable heat from grass/straw used: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	0.025	0.002	0.022	0.025
	Renewable heat from biogas used: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	0.000	0.000	0.000	0.000
	Refrigerant losses - HGC 134a: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	1430.000	65.000	1300	1430
	Refrigerant losses - R404a: EF	DEFRA/DECC (2015)	DEFRA/DECC (2012-2015)	Beta PERT	3921.600	330.800	3260	3922
	Transport: EF	DEFRA/DECC (2015)	DEFRA/DECC (2015)	Beta PERT	0.914	0.157	0.565	0.999
Embedded emissions	Urea [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	5	-	4.41	5.63
	Urea [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.49	-	3.06	3.88
	Urea [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.82	-	4.41	5.36
	Urea [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.75	-	3.29	4.17

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Urea [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.41	-	6.64	8.34
	Urea [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.63	-	3.18	4.18
	Liquid UAN [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.27	-	2.65	16.75
	Liquid UAN [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	5.77	-	2.11	10.38
	Liquid UAN [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.08	-	4.51	14.11
	Liquid UAN [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	6.04	-	2.74	12.79
	Liquid UAN [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	9.65	-	5.23	17.12
	Liquid UAN [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	5.91	-	3.49	13.62
	Anhydrous ammonia [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.21	-	3.27	5.29
	Anhydrous ammonia [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	2.85	-	2.19	3.44
	Anhydrous ammonia [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.04	-	3.44	4.98
	Anhydrous ammonia [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.11	-	2.4	3.75
	Anhydrous ammonia [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	6.36	-	5.16	7.98
	Anhydrous ammonia [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	2.99	-	2.3	3.89
	Ammonium nitrate [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	9.47	-	6.6	14.14

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Ammonium nitrate [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.99	-	5.25	10.04
	Ammonium nitrate [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	9.28	-	7.94	13.89
	Ammonium nitrate [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.27	-	6.15	12.76
	Ammonium nitrate [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	11.8	-	10.18	16.71
	Ammonium nitrate [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.14	-	6.77	12.73
	CAN [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	9.51	-	6.65	14.18
	CAN [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.03	-	5.29	10.08
	CAN [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	9.33	-	7.98	13.93
	CAN [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.31	-	6.18	12.79
	CAN [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	11.86	-	10.24	16.77
	CAN [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.18	-	6.8	12.76
	Ammonium Sulphate [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.33	-	0.94	6.23
	Ammonium Sulphate [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	2.14	-	0.75	4.67
	Ammonium Sulphate [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.18	-	1.37	5.84
	Ammonium Sulphate [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	2.4	-	0.75	4.67

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Ammonium Sulphate [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	5.2	-	1.69	8.17
	Ammonium Sulphate [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	2.28	-	0.75	5.46
	MAP [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.75	-	1.21	6.42
	MAP [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.29	-	0.47	4.52
	MAP [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.57	-	1.27	6.14
	MAP [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.55	-	0.71	4.8
	MAP [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.06	-	2.42	9.37
	MAP [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.42	-	0.6	4.81
	DAP [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.52	-	2.39	5.67
	DAP [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.1	-	1.43	3.9
	DAP [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.34	-	2.42	5.41
	DAP [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.36	-	1.66	4.19
	DAP [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	6.76	-	3.97	8.38
	DAP [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.24	-	1.55	4.2
	NPK (AN, AP and MOP) [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	9.12	-	7.57	11.14
	NPK (AN, AP and MOP) [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.47	-	6.06	8.44

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	NPK (AN, AP and MOP) [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.92	-	7.97	10.89
	NPK (AN, AP and MOP) [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.75	-	6.57	9.64
	NPK (AN, AP and MOP) [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	11.75	-	10.5	13.96
	NPK (AN, AP and MOP) [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	7.62	-	6.72	9.57
	NPK (Urea, TSP & MOP) [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	6.19	-	5.54	6.68
	NPK (Urea, TSP & MOP) [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.45	-	3.94	4.8
	NPK (Urea, TSP & MOP) [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	5.98	-	5.44	6.41
	NPK (Urea, TSP & MOP) [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.71	-	4.19	5.08
	NPK (Urea, TSP & MOP) [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	8.98	-	8.11	9.67
	NPK (Urea, TSP & MOP) [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4.59	-	4.08	5.02
	NK (Nitric acid and MOP) [World average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	19.6	-	14.1	28.4
	NK (Nitric acid and MOP) [Western Europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	17.1	-	11.7	21.1
	NK (Nitric acid and MOP) [Russia + central europe] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	19.3	-	16.7	27.9

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	NK (Nitric acid and MOP) [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	17.3	-	13.2	26.1
	NK (Nitric acid and MOP) [China + India] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	23.7	-	20.5	32.8
	NK (Nitric acid and MOP) [Rest of world] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	17.2	-	14.5	26
	Triple Super Phosphate [World average] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.45	-	0	0.63
	Triple Super Phosphate [Western Europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.36	-	0	0.52
	Triple Super Phosphate [Russia + central europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.44	-	0	0.61
	Triple Super Phosphate [North America] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.36	-	0	0.52
	Triple Super Phosphate [China + India] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.59	-	0	0.83
	Triple Super Phosphate [Rest of world] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.36	-	0	0.52
	Single Super Phosphate [World average] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.16	-	0	0.56
	Single Super Phosphate [Western Europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.13	-	0	0.47
	Single Super Phosphate [Russia + central europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.16	-	0	0.53

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Single Super Phosphate [North America] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.13	-	0	0.47
	Single Super Phosphate [China + India] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.21	-	0	0.74
	Single Super Phosphate [Rest of world] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.13	-	0	0.47
	Ground rock [World average] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.23	-	0.02	0.26
	Ground rock [Western Europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.19	-	0.02	0.23
	Ground rock [Russia + central europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.23	-	0.02	0.24
	Ground rock [North America] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.19	-	0.02	0.23
	Ground rock [China + India] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.31	-	0.03	0.34
	Ground rock [Rest of world] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.19	-	0.02	0.23
	PK [World average] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.19	-	0.84	1.37
	PK [Western Europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.97	-	0.67	1.13
	PK [Russia + central europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.17	-	0.83	1.33
	PK [North America] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.97	-	0.67	1.13
	PK [China + India] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.57	-	1.09	1.8
	PK [Rest of world] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.97	-	0.67	1.13

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Potassium Chloride [World average] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.69	-	0.48	0.85
	Potassium Chloride [Western Europe] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.56	-	0.39	0.71
	Potassium Chloride [Russia + central europe] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.68	-	0.49	0.82
	Potassium Chloride [North America] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.56	-	0.39	0.71
	Potassium Chloride [China + India] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.91	-	0.62	1.12
	Potassium Chloride [Rest of world] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.56	-	0.39	0.71
	Potassium Sulphate [World average] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.23	-	0.06	0.28
	Potassium Sulphate [Western Europe] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.19	-	0.05	0.23
	Potassium Sulphate [Russia + central europe] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.23	-	0.16	0.28
	Potassium Sulphate [North America] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.19	-	0.05	0.23
	Potassium Sulphate [China + India] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.31	-	0.08	0.37
	Potassium Sulphate [Rest of world] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.19	-	0.05	0.23
	Other N-fertilizer [Global average] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	5.66	-	3.42	8.43
	Other N-fertilizer [Western Europe] kg CO2-eq / kg N	***Kool et al. (2012)***	***Kool et al. (2012)***	***Beta PERT***	***5.62***	***-***	***3.05***	***7.27***

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Other N-fertilizer [Eastern Europe (+ Russia)] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	6.87	-	5.61	7.24
	Other N-fertilizer [South America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.53	-	2.53	4.47
	Other N-fertilizer [North America] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	4	-	2.32	5.06
	Other N-fertilizer [Asia] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	6.92	-	5.56	8.26
	Other N-fertilizer [Australia] kg CO2-eq / kg N	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	3.06	-	2.16	4.45
	Other P2O5 fertilizer [Global average] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.36	-	0.14	2.15
	Other P2O5 fertilizer [Western Europe] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.47	-	0	2.49
	Other P2O5 fertilizer [Eastern Europe (+ Russia)] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.57	-	0.42	2.44
	Other P2O5 fertilizer [South America] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.54	-	0	0.85
	Other P2O5 fertilizer [North America] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.29	-	0.12	2.11
	Other P2O5 fertilizer [Asia] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.66	-	0.41	2.52
	Other P2O5 fertilizer [Australia] kg CO2-eq / kg P2O5	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.14	-	0.09	1.97
	Other K2O fertilizer [Global average] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.23	-	0.36	1.91
	Other K2O fertilizer [Western Europe] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.36	-	0	2.31

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Other K2O fertilizer [Eastern Europe (+ Russia)] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.45	-	0.41	2.34
	Other K2O fertilizer [South America] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.61	-	0.4	0.83
	Other K2O fertilizer [North America] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.02	-	0.21	1.71
	Other K2O fertilizer [Asia] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.47	-	0.71	2.07
	Other K2O fertilizer [Australia] kg CO2-eq / kg K2O	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	1.63	-	0	3.22
	Lime [Global average] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime [Western Europe] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime [Eastern Europe (+ Russia)] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime [South America] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime [North America] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime [Asia] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime [Australia] kg CO2-eq / kg product	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Lime embedded EF	Kool et al. (2012)	Kool et al. (2012)	Beta PERT	0.074	-	0.054	0.089
	Herbicide embedded EF (/kg a.i.)	***Audsley et al. (2009)***	***Audsley et al. (2009)***	***Uniform***	***29.545***	***11.676***	***7.383***	***47.679***
	Insecticide embedded EF (/kg a.i.)	Audsley et al. (2009)	Audsley et al. (2009)	Uniform	28.463	11.020	10.212	42.435
	Fungicide embedded EF (/kg a.i.)	Audsley et al. (2009)	Audsley et al. (2009)	Uniform	37.580	8.396	19.320	49.197

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Generic/other pesticide embedded EF (/kg a.i.)	Audsley et al. (2009)	Audsley et al. (2009)	Uniform	31.950	11.190	7.383	49.197
	Herbicide application rate: Rough Grazing	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	2.360	-	1.888	2.832
	Herbicide application rate: Pasture grazing	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	1.151	-	0.921	1.381
	Herbicide application rate: Silage & graze	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	1.174	-	0.939	1.409
	Herbicide application rate: Hay & graze	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	1.174	-	0.939	1.409
	Herbicide application rate: Kale / stubble turnips etc	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.595	-	0.476	0.714
	Herbicide application rate: Fodder beet	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	3.780	-	3.024	4.536
	Herbicide application rate: Wholecrop cereals	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	1.366	-	1.093	1.639
	Herbicide application rate: Forage maize	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	1.500	-	1.200	1.800
	Herbicide application rate: Legume forages	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	2.770	-	2.216	3.324
	Herbicide application rate: Feed wheat	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.543	-	1.234	1.852
	Herbicide application rate: Milling wheat	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.543	-	1.234	1.852
	Herbicide application rate: Feed winter barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.559	-	1.247	1.871
	Herbicide application rate: Malting winter barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.559	-	1.247	1.871
	Herbicide application rate: Feed spring barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.854	-	0.683	1.025
	Herbicide application rate: Malting spring barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.854	-	0.683	1.025
	Herbicide application rate: Winter oats	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.549	-	0.439	0.659

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Herbicide application rate: Spring oats	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.549	-	0.439	0.659
	Herbicide application rate: Minor cereals (rye, triticale)	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.896	-	0.717	1.075
	Herbicide application rate: Oilseed rape	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.540	-	0.432	0.648
	Herbicide application rate: Field beans	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.112	-	0.090	0.134
	Herbicide application rate: Field peas	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.490	-	0.392	0.588
	Herbicide application rate: Seed potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.182	-	1.746	2.618
	Herbicide application rate: Early potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.182	-	1.746	2.618
	Herbicide application rate: Maincrop ware potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.911	-	2.329	3.493
	Herbicide application rate: Maincrop processing potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.911	-	2.329	3.493
	Herbicide application rate: Sugar beet	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	3.268	-	2.614	3.922
	Herbicide application rate: Swedes / turnips	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.881	-	0.705	1.057
	Herbicide application rate: Carrots	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	6.313	-	5.050	7.576
	Herbicide application rate: Other root veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	65.540	-	52.432	78.648
	Herbicide application rate: Processing peas	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.454	-	1.963	2.945
	Herbicide application rate: Processing beans	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.254	-	1.803	2.705
	Herbicide application rate: Other legume veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	2.770	-	2.216	3.324
	Herbicide application rate: Cabbages	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.839	-	1.471	2.207

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Herbicide application rate: Cauliflower	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.839	-	1.471	2.207
	Herbicide application rate: Calabrese	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.839	-	1.471	2.207
	Herbicide application rate: Brussel sprouts	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.839	-	1.471	2.207
	Herbicide application rate: Other brassica veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.839	-	1.471	2.207
	Herbicide application rate: Lettuce	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	2.363	-	1.890	2.836
	Herbicide application rate: Onions / leeks	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	3.840	-	3.072	4.608
	Herbicide application rate: Strawberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	3.590	-	2.872	4.308
	Herbicide application rate: Raspberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	2.228	-	1.782	2.674
	Herbicide application rate: Blueberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	1.423	-	1.138	1.708
	Herbicide application rate: Blackberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	1.590	-	1.272	1.908
	Herbicide application rate: Top fruit	Garthwaite et al. (2012a)	Marinussen et al. (2012)	Uniform	1.470	-	1.176	1.764
	Herbicide application rate: Bulbs	Garthwaite et al. (2009)	Marinussen et al. (2012)	Uniform	3.150	-	2.520	3.780
	Herbicide application rate: Fibre crops	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.130	-	0.904	1.356
	Insecticide application rate: Rough Grazing	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.190	-	0.152	0.228
	Insecticide application rate: Pasture grazing	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.231	-	0.185	0.277
	Insecticide application rate: Silage & graze	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.547	-	0.438	0.656
	Insecticide application rate: Hay & graze	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.547	-	0.438	0.656
	Insecticide application rate: Kale / stubble turnips etc	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.310	-	0.248	0.372

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Insecticide application rate: Fodder beet	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.159	-	0.127	0.191
	Insecticide application rate: Wholecrop cereals	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.050	-	0.040	0.060
	Insecticide application rate: Forage maize	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.221	-	0.177	0.265
	Insecticide application rate: Legume forages	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.122	-	0.098	0.146
	Insecticide application rate: Feed wheat	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.570	-	0.456	0.684
	Insecticide application rate: Milling wheat	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.570	-	0.456	0.684
	Insecticide application rate: Feed winter barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.230	-	0.184	0.276
	Insecticide application rate: Malting winter barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.230	-	0.184	0.276
	Insecticide application rate: Feed spring barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.510	-	0.408	0.612
	Insecticide application rate: Malting spring barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.510	-	0.408	0.612
	Insecticide application rate: Winter oats	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.190	-	0.152	0.228
	Insecticide application rate: Spring oats	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.190	-	0.152	0.228
	Insecticide application rate: Minor cereals (rye, triticale)	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.017	-	0.014	0.020
	Insecticide application rate: Oilseed rape	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.662	-	0.530	0.794
	Insecticide application rate: Field beans	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.755	-	0.604	0.906
	Insecticide application rate: Field peas	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.111	-	0.889	1.333
	Insecticide application rate: Seed potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.338	-	0.270	0.406

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Insecticide application rate: Early potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.338	-	0.270	0.406
	Insecticide application rate: Maincrop ware potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.568	-	1.254	1.882
	Insecticide application rate: Maincrop processing potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.568	-	1.254	1.882
	Insecticide application rate: Sugar beet	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.268	-	0.214	0.322
	Insecticide application rate: Swedes / turnips	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.032	-	0.026	0.038
	Insecticide application rate: Carrots	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.419	-	1.135	1.703
	Insecticide application rate: Other root veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.880	-	0.704	1.056
	Insecticide application rate: Processing peas	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.112	-	0.090	0.134
	Insecticide application rate: Processing beans	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.490	-	0.392	0.588
	Insecticide application rate: Other legume veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.122	-	0.098	0.146
	Insecticide application rate: Cabbages	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.860	-	0.688	1.032
	Insecticide application rate: Cauliflower	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.860	-	0.688	1.032
	Insecticide application rate: Calabrese	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.860	-	0.688	1.032
	Insecticide application rate: Brussel sprouts	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.860	-	0.688	1.032
	Insecticide application rate: Other brassica veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.860	-	0.688	1.032
	Insecticide application rate: Lettuce	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.257	-	0.206	0.308
	Insecticide application rate: Onions / leeks	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.354	-	0.283	0.425

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Insecticide application rate: Strawberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	1.210	-	0.968	1.452
	Insecticide application rate: Raspberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	0.691	-	0.553	0.829
	Insecticide application rate: Blueberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	0.747	-	0.598	0.896
	Insecticide application rate: Blackberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	0.683	-	0.546	0.820
	Insecticide application rate: Top fruit	Garthwaite et al. (2012a)	Marinussen et al. (2012)	Uniform	1.350	-	1.080	1.620
	Insecticide application rate: Bulbs	Garthwaite et al. (2009)	Marinussen et al. (2012)	Uniform	0.660	-	0.528	0.792
	Insecticide application rate: Fibre crops	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.370	-	0.296	0.444
	Fungicide application rate: Fodder beet	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.117	-	0.094	0.140
	Fungicide application rate: Wholecrop cereals	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	1.051	-	0.841	1.261
	Fungicide application rate: Forage maize	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.420	-	0.336	0.504
	Fungicide application rate: Legume forages	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.521	-	0.417	0.625
	Fungicide application rate: Feed wheat	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.294	-	1.035	1.553
	Fungicide application rate: Milling wheat	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.294	-	1.035	1.553
	Fungicide application rate: Feed winter barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.727	-	0.582	0.872
	Fungicide application rate: Malting winter barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.727	-	0.582	0.872
	Fungicide application rate: Feed spring barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.621	-	0.497	0.745
	Fungicide application rate: Malting spring barley	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.621	-	0.497	0.745

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Fungicide application rate: Winter oats	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.450	-	0.360	0.540
	Fungicide application rate: Spring oats	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.450	-	0.360	0.540
	Fungicide application rate: Minor cereals (rye, triticale)	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.354	-	0.283	0.425
	Fungicide application rate: Oilseed rape	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.825	-	1.460	2.190
	Fungicide application rate: Field beans	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.454	-	1.963	2.945
	Fungicide application rate: Field peas	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	2.254	-	1.803	2.705
	Fungicide application rate: Seed potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	4.969	-	3.975	5.963
	Fungicide application rate: Early potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	4.969	-	3.975	5.963
	Fungicide application rate: Maincrop ware potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	8.546	-	6.837	10.255
	Fungicide application rate: Maincrop processing potatoes	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	8.546	-	6.837	10.255
	Fungicide application rate: Sugar beet	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.424	-	0.339	0.509
	Fungicide application rate: Swedes / turnips	Garthwaite et al. (2013a)	Marinussen et al. (2012)	Uniform	0.022	-	0.018	0.026
	Fungicide application rate: Carrots	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	2.134	-	1.707	2.561
	Fungicide application rate: Other root veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	2.176	-	1.741	2.611
	Fungicide application rate: Processing peas	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.755	-	0.604	0.906
	Fungicide application rate: Processing beans	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	1.111	-	0.889	1.333
	Fungicide application rate: Other legume veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	0.521	-	0.417	0.625

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Fungicide application rate: Cabbages	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.500	-	1.200	1.800
	Fungicide application rate: Cauliflower	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.500	-	1.200	1.800
	Fungicide application rate: Calabrese	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.500	-	1.200	1.800
	Fungicide application rate: Brussel sprouts	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.500	-	1.200	1.800
	Fungicide application rate: Other brassica veg	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	1.500	-	1.200	1.800
	Fungicide application rate: Lettuce	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	3.360	-	2.688	4.032
	Fungicide application rate: Onions / leeks	Garthwaite et al. (2013b)	Marinussen et al. (2012)	Uniform	8.987	-	7.190	10.784
	Fungicide application rate: Strawberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	13.912	-	11.130	16.694
	Fungicide application rate: Raspberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	2.636	-	2.109	3.163
	Fungicide application rate: Blueberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	1.943	-	1.554	2.332
	Fungicide application rate: Blackberries	Garthwaite et al. (2012b)	Marinussen et al. (2012)	Uniform	2.840	-	2.272	3.408
	Fungicide application rate: Top fruit	Garthwaite et al. (2012a)	Marinussen et al. (2012)	Uniform	14.779	-	11.823	17.735
	Fungicide application rate: Bulbs	Garthwaite et al. (2009)	Marinussen et al. (2012)	Uniform	3.629	-	2.903	4.355
	Fungicide application rate: Fibre crops	Garthwaite et al. (2012c)	Marinussen et al. (2012)	Uniform	0.284	-	0.227	0.341
Livestock ration paramters	***All beef classes Grazing GE***	***Stergiadis et al. (2015)***	***Stergiadis et al. (2015)***	***Normal***	***18.300***	***0.380***	-	-
	Homegrown: Silage & graze DM	Feedipedia (2012)	Feedipedia (2012)	Normal	31.733	2.542	-	-
	Homegrown: Hay & graze DM	Feedipedia (2012)	Feedipedia (2012)	Normal	88.550	2.017	-	-
	Homegrown: Kale / stubble turnips / swedes / etc DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Fodder beet DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.300	2.200	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Wholecrop cereals DM	Feedipedia (2012)	Feedipedia (2012)	Normal	27.225	3.325	-	-
	Homegrown: Forage maize DM	Feedipedia (2012)	Feedipedia (2012)	Normal	28.200	1.300	-	-
	Homegrown: Legume forages (clovers, lucerne) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	18.350	3.737	-	-
	Homegrown: Feed wheat DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.000	1.300	-	-
	Homegrown: Feed wheat (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Milling wheat DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.000	1.300	-	-
	Homegrown: Milling wheat (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Feed winter barley DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.300	-	-
	Homegrown: Feed winter barley (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Malting winter barley DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.300	-	-
	Homegrown: Malting winter barley (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Feed spring barley DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.300	-	-
	Homegrown: Feed spring barley (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Malting spring barley DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.300	-	-
	Homegrown: Malting spring barley (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Winter oats DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.900	1.400	-	-
	Homegrown: Winter oats (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Spring oats DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.900	1.400	-	-
	Homegrown: Spring oats (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Minor cereals DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.850	0.791	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Minor cereals (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Oilseed rape DM	Feedipedia (2012)	Feedipedia (2012)	Normal	90.867	1.650	-	-
	Homegrown: Oilseed rape (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Field beans DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.600	1.400	-	-
	Homegrown: Field beans (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Field peas DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.500	1.200	-	-
	Homegrown: Field peas (straw) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	1.300	-	-
	Homegrown: Seed potatoes DM	Feedipedia (2012)	Feedipedia (2012)	Normal	20.200	1.300	-	-
	Homegrown: Early potatoes DM	Feedipedia (2012)	Feedipedia (2012)	Normal	20.200	1.300	-	-
	Homegrown: Maincrop ware potatoes DM	Feedipedia (2012)	Feedipedia (2012)	Normal	20.200	1.300	-	-
	Homegrown: Maincrop processing potatoes DM	Feedipedia (2012)	Feedipedia (2012)	Normal	20.200	1.300	-	-
	Homegrown: Sugar beet DM	Feedipedia (2012)	Feedipedia (2012)	Normal	18.800	4.200	-	-
	Homegrown: Swedes / turnips DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Carrots DM	Feedipedia (2012)	Feedipedia (2012)	Normal	10.700	1.500	-	-
	Homegrown: Other root veg DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Processing peas DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.500	1.200	-	-
	Homegrown: Processing beans DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.600	1.400	-	-
	Homegrown: Other legume veg DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.550	0.922	-	-
	Homegrown: Cabbages DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Cauliflower DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Calabrese DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Brussel sprouts DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Other brassica veg DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.567	1.548	-	-
	Homegrown: Silage & graze CP	Feedipedia (2012)	Feedipedia (2012)	Normal	8.800	0.935	-	-
	Homegrown: Hay & graze CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.080	1.264	-	-
	Homegrown: Kale / stubble turnips / swedes / etc CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Fodder beet CP	Feedipedia (2012)	Feedipedia (2012)	Normal	6.700	1.100	-	-
	Homegrown: Wholecrop cereals CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.175	1.952	-	-
	Homegrown: Forage maize CP	Feedipedia (2012)	Feedipedia (2012)	Normal	7.300	0.900	-	-
	Homegrown: Legume forages (clovers, lucerne) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	22.750	2.171	-	-
	Homegrown: Feed wheat CP	Feedipedia (2012)	Feedipedia (2012)	Normal	12.600	1.300	-	-
	Homegrown: Feed wheat (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Milling wheat CP	Feedipedia (2012)	Feedipedia (2012)	Normal	12.600	1.300	-	-
	Homegrown: Milling wheat (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Feed winter barley CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.800	1.100	-	-
	Homegrown: Feed winter barley (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Malting winter barley CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.800	1.100	-	-
	Homegrown: Malting winter barley (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Feed spring barley CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.800	1.100	-	-
	Homegrown: Feed spring barley (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Malting spring barley CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.800	1.100	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Malting spring barley (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Winter oats CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.000	1.400	-	-
	Homegrown: Winter oats (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Spring oats CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.000	1.400	-	-
	Homegrown: Spring oats (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Minor cereals CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.000	0.820	-	-
	Homegrown: Minor cereals (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Oilseed rape CP	Feedipedia (2012)	Feedipedia (2012)	Normal	37.600	2.150	-	-
	Homegrown: Oilseed rape (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Field beans CP	Feedipedia (2012)	Feedipedia (2012)	Normal	29.000	1.800	-	-
	Homegrown: Field beans (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Field peas CP	Feedipedia (2012)	Feedipedia (2012)	Normal	23.900	1.400	-	-
	Homegrown: Field peas (straw) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	4.200	0.700	-	-
	Homegrown: Seed potatoes CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.800	0.700	-	-
	Homegrown: Early potatoes CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.800	0.700	-	-
	Homegrown: Maincrop ware potatoes CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.800	0.700	-	-
	Homegrown: Maincrop processing potatoes CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.800	0.700	-	-
	Homegrown: Sugar beet CP	Feedipedia (2012)	Feedipedia (2012)	Normal	7.800	1.500	-	-
	Homegrown: Swedes / turnips CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Carrots CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.100	3.200	-	-
	Homegrown: Other root veg CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Processing peas CP	Feedipedia (2012)	Feedipedia (2012)	Normal	23.900	1.400	-	-
	Homegrown: Processing beans CP	Feedipedia (2012)	Feedipedia (2012)	Normal	29.000	1.800	-	-
	Homegrown: Other legume veg CP	Feedipedia (2012)	Feedipedia (2012)	Normal	26.450	1.140	-	-
	Homegrown: Cabbages CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Cauliflower CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Calabrese CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Brussel sprouts CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Other brassica veg CP	Feedipedia (2012)	Feedipedia (2012)	Normal	9.233	1.201	-	-
	Homegrown: Silage & graze GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.650	0.695	-	-
	Homegrown: Hay & graze GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.920	0.267	-	-
	Homegrown: Kale / stubble turnips / swedes / etc GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Fodder beet GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.700	0.400	-	-
	Homegrown: Wholecrop cereals GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.825	0.265	-	-
	Homegrown: Forage maize GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.000	0.100	-	-
	Homegrown: Legume forages (clovers, lucerne) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.200	0.640	-	-
	Homegrown: Feed wheat GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.200	0.200	-	-
	Homegrown: Feed wheat (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Milling wheat GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.200	0.200	-	-
	Homegrown: Milling wheat (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Feed winter barley GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.400	0.100	-	-
	Homegrown: Feed winter barley (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Malting winter barley GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.400	0.100	-	-
	Homegrown: Malting winter barley (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Feed spring barley GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.400	0.100	-	-
	Homegrown: Feed spring barley (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Malting spring barley GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.400	0.100	-	-
	Homegrown: Malting spring barley (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Winter oats GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.500	0.200	-	-
	Homegrown: Winter oats (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Spring oats GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.500	0.200	-	-
	Homegrown: Spring oats (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Minor cereals GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.050	0.112	-	-
	Homegrown: Minor cereals (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Oilseed rape GE	Feedipedia (2012)	Feedipedia (2012)	Normal	20.267	0.800	-	-
	Homegrown: Oilseed rape (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Field beans GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.700	0.200	-	-
	Homegrown: Field beans (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Field peas GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.300	0.100	-	-
	Homegrown: Field peas (straw) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.600	-	-
	Homegrown: Seed potatoes GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	0.200	-	-
	Homegrown: Early potatoes GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	0.200	-	-
	Homegrown: Maincrop ware potatoes GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	0.200	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Maincrop processing potatoes GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	0.200	-	-
	Homegrown: Sugar beet GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	-	-	-
	Homegrown: Swedes / turnips GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Carrots GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.100	-	-	-
	Homegrown: Other root veg GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Processing peas GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.300	0.100	-	-
	Homegrown: Processing beans GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.700	0.200	-	-
	Homegrown: Other legume veg GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.500	0.112	-	-
	Homegrown: Cabbages GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Cauliflower GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Calabrese GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Brussel sprouts GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Other brassica veg GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.967	0.200	-	-
	Homegrown: Silage & graze DE	Feedipedia (2012)	Feedipedia (2012)	Normal	60.767	2.400	-	-
	Homegrown: Hay & graze DE	Feedipedia (2012)	Feedipedia (2012)	Normal	58.100	4.728	-	-
	Homegrown: Kale / stubble turnips / swedes / etc DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Fodder beet DE	Feedipedia (2012)	Feedipedia (2012)	Normal	84.600	1.600	-	-
	Homegrown: Wholecrop cereals DE	Feedipedia (2012)	Feedipedia (2012)	Normal	64.125	5.218	-	-
	Homegrown: Forage maize DE	Feedipedia (2012)	Feedipedia (2012)	Normal	68.600	2.300	-	-
	Homegrown: Legume forages (clovers, lucerne) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	71.400	8.800	-	-
	Homegrown: Feed wheat DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.700	2.700	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Feed wheat (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Milling wheat DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.700	2.700	-	-
	Homegrown: Milling wheat (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Feed winter barley DE	Feedipedia (2012)	Feedipedia (2012)	Normal	80.700	2.140	-	-
	Homegrown: Feed winter barley (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Malting winter barley DE	Feedipedia (2012)	Feedipedia (2012)	Normal	80.700	2.140	-	-
	Homegrown: Malting winter barley (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Feed spring barley DE	Feedipedia (2012)	Feedipedia (2012)	Normal	80.700	2.140	-	-
	Homegrown: Feed spring barley (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Malting spring barley DE	Feedipedia (2012)	Feedipedia (2012)	Normal	80.700	2.140	-	-
	Homegrown: Malting spring barley (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Winter oats DE	Feedipedia (2012)	Feedipedia (2012)	Normal	75.500	3.500	-	-
	Homegrown: Winter oats (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Spring oats DE	Feedipedia (2012)	Feedipedia (2012)	Normal	75.500	3.500	-	-
	Homegrown: Spring oats (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Minor cereals DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.750	6.978	-	-
	Homegrown: Minor cereals (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Oilseed rape DE	Feedipedia (2012)	Feedipedia (2012)	Normal	78.500	6.388	-	-
	Homegrown: Oilseed rape (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Field beans DE	Feedipedia (2012)	Feedipedia (2012)	Normal	89.800	3.000	-	-
	Homegrown: Field beans (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Homegrown: Field peas DE	Feedipedia (2012)	Feedipedia (2012)	Normal	90.300	1.700	-	-
	Homegrown: Field peas (straw) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	45.200	3.678	-	-
	Homegrown: Seed potatoes DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.600	-	-
	Homegrown: Early potatoes DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.600	-	-
	Homegrown: Maincrop ware potatoes DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.600	-	-
	Homegrown: Maincrop processing potatoes DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.600	-	-
	Homegrown: Sugar beet DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.600	7.129	-	-
	Homegrown: Swedes / turnips DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Carrots DE	Feedipedia (2012)	Feedipedia (2012)	Normal	83.100	6.762	-	-
	Homegrown: Other root veg DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Processing peas DE	Feedipedia (2012)	Feedipedia (2012)	Normal	90.300	1.700	-	-
	Homegrown: Processing beans DE	Feedipedia (2012)	Feedipedia (2012)	Normal	89.800	3.000	-	-
	Homegrown: Other legume veg DE	Feedipedia (2012)	Feedipedia (2012)	Normal	90.050	1.724	-	-
	Homegrown: Cabbages DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Cauliflower DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Calabrese DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Brussel sprouts DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Homegrown: Other brassica veg DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.933	1.600	-	-
	Purchased: Hay DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***88.550***	***2.017***	-	-
	Purchased: Grass silage DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***31.733***	***2.542***	-	-
	Purchased: Wholecrop cereals DM	Feedipedia (2012)	Feedipedia (2012)	Normal	27.225	3.325	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Purchased: Maize silage DM	Feedipedia (2012)	Feedipedia (2012)	Normal	28.200	1.300	-	-
	Purchased: Straw DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***91.000***	***1.300***	-	-
	Purchased: Clover silage DM	Feedipedia (2012)	Feedipedia (2012)	Normal	27.700	6.400	-	-
	Purchased: Fodder beet DM	Feedipedia (2012)	Feedipedia (2012)	Normal	16.300	2.200	-	-
	Purchased: Lucerne DM	Feedipedia (2012)	Feedipedia (2012)	Normal	19.900	3.100	-	-
	Purchased: Brewers grains DM	Feedipedia (2012)	Feedipedia (2012)	Normal	91.000	2.500	-	-
	Purchased: Citrus pulp DM	Feedipedia (2012)	Feedipedia (2012)	Normal	89.600	1.200	-	-
	Purchased: Wheat (grain) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.000	1.300	-	-
	Purchased: Barley (grain) DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***87.100***	***1.300***	-	-
	Purchased: Oats (grain) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.900	1.400	-	-
	Purchased: Potatoes (brock) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	20.200	1.300	-	-
	Purchased: Potatoes (ware) DM	Feedipedia (2012)	Feedipedia (2012)	Normal	20.200	1.300	-	-
	Purchased: Soya meal DM	Feedipedia (2012)	Feedipedia (2012)	Normal	87.900	0.900	-	-
	Purchased: Rape Meal DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***90.867***	***1.209***	-	-
	Purchased: Distillers Pellets DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***90.700***	***1.900***	-	-
	Purchased: Maize gluten DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***88.300***	***1.500***	-	-
	Purchased: Molasses DM	Feedipedia (2012)	Feedipedia (2012)	Normal	73.000	1.800	-	-
	Purchased: Beef and calf nuts DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***86.153***	***0.884***	-	-
	Purchased: Ewe and lamb nuts DM	Feedipedia (2012)	Feedipedia (2012)	Normal	80.005	0.959	-	-
	Purchased: Dairy and calf nuts DM	Feedipedia (2012)	Feedipedia (2012)	Normal	83.729	0.685	-	-
	Purchased: Milk powder DM	Feedipedia (2012)	Feedipedia (2012)	Normal	94.500	4.725	-	-
	Purchased: Minerals DM	Feedipedia (2012)	Feedipedia (2012)	Normal	100.000	0.000	-	-
	Purchased: Field beans DM	Feedipedia (2012)	Feedipedia (2012)	Normal	86.600	1.400	-	-
	Purchased: Waste vegetables DM	Feedipedia (2012)	Feedipedia (2012)	Normal	23.175	1.213	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Purchased: Sugar beet pulp DM	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***89.200***	***1.300***	-	-
	Purchased: Hay CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***10.080***	***1.264***	-	-
	Purchased: Grass silage CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***8.800***	***0.935***	-	-
	Purchased: Wholecrop cereals CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.175	1.952	-	-
	Purchased: Maize silage CP	Feedipedia (2012)	Feedipedia (2012)	Normal	7.300	0.900	-	-
	Purchased: Straw CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***4.200***	***0.700***	-	-
	Purchased: Clover silage CP	Feedipedia (2012)	Feedipedia (2012)	Normal	18.900	2.300	-	-
	Purchased: Fodder beet CP	Feedipedia (2012)	Feedipedia (2012)	Normal	6.700	1.100	-	-
	Purchased: Lucerne CP	Feedipedia (2012)	Feedipedia (2012)	Normal	20.600	3.400	-	-
	Purchased: Brewers grains CP	Feedipedia (2012)	Feedipedia (2012)	Normal	25.800	3.100	-	-
	Purchased: Citrus pulp CP	Feedipedia (2012)	Feedipedia (2012)	Normal	7.000	0.600	-	-
	Purchased: Wheat (grain) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	12.600	1.300	-	-
	Purchased: Barley (grain) CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***11.800***	***1.100***	-	-
	Purchased: Oats (grain) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	11.000	1.400	-	-
	Purchased: Potatoes (brock) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.800	0.700	-	-
	Purchased: Potatoes (ware) CP	Feedipedia (2012)	Feedipedia (2012)	Normal	10.800	0.700	-	-
	Purchased: Soya meal CP	Feedipedia (2012)	Feedipedia (2012)	Normal	51.800	1.800	-	-
	Purchased: Rape Meal CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***37.600***	***1.524***	-	-
	Purchased: Distillers Pellets CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***27.800***	***2.100***	-	-
	Purchased: Maize gluten CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***21.700***	***1.500***	-	-
	Purchased: Molasses CP	Feedipedia (2012)	Feedipedia (2012)	Normal	5.500	1.400	-	-
	Purchased: Beef and calf nuts CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***18.208***	***0.782***	-	-
	Purchased: Ewe and lamb nuts CP	Feedipedia (2012)	Feedipedia (2012)	Normal	20.214	0.841	-	-
	Purchased: Dairy and calf nuts CP	Feedipedia (2012)	Feedipedia (2012)	Normal	22.286	0.670	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Purchased: Milk powder CP	Feedipedia (2012)	Feedipedia (2012)	Normal	35.000	1.750	-	-
	Purchased: Minerals CP	Feedipedia (2012)	Feedipedia (2012)	Normal	0.000	0.000	-	-
	Purchased: Field beans CP	Feedipedia (2012)	Feedipedia (2012)	Normal	29.000	1.800	-	-
	Purchased: Waste vegetables CP	Feedipedia (2012)	Feedipedia (2012)	Normal	15.900	1.334	-	-
	Purchased: Sugar beet pulp CP	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***9.300***	***0.900***	-	-
	Purchased: Hay GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***17.920***	***0.267***	-	-
	Purchased: Grass silage GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***17.650***	***0.695***	-	-
	Purchased: Wholecrop cereals GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.825	0.265	-	-
	Purchased: Maize silage GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.000	0.100	-	-
	Purchased: Straw GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***18.500***	***0.600***	-	-
	Purchased: Clover silage GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.900	0.500	-	-
	Purchased: Fodder beet GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.700	0.400	-	-
	Purchased: Lucerne GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.100	1.000	-	-
	Purchased: Brewers grains GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.700	1.800	-	-
	Purchased: Citrus pulp GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.300	0.300	-	-
	Purchased: Wheat (grain) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.200	0.200	-	-
	Purchased: Barley (grain) GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***18.400***	***0.100***	-	-
	Purchased: Oats (grain) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.500	0.200	-	-
	Purchased: Potatoes (brock) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	0.200	-	-
	Purchased: Potatoes (ware) GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.900	0.200	-	-
	Purchased: Soya meal GE	Feedipedia (2012)	Feedipedia (2012)	Normal	19.700	0.300	-	-
	Purchased: Rape Meal GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***20.267***	***0.583***	-	-
	Purchased: Distillers Pellets GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***21.300***	***0.600***	-	-
	Purchased: Maize gluten GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***18.800***	***0.300***	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Purchased: Molasses GE	Feedipedia (2012)	Feedipedia (2012)	Normal	14.700	0.600	-	-
	Purchased: Beef and calf nuts GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***18.419***	***0.103***	-	-
	Purchased: Ewe and lamb nuts GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.115	0.103	-	-
	Purchased: Dairy and calf nuts GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.398	0.124	-	-
	Purchased: Milk powder GE	Feedipedia (2012)	Feedipedia (2012)	Normal	16.100	0.805	-	-
	Purchased: Minerals GE	Feedipedia (2012)	Feedipedia (2012)	Normal	0.000	0.000	-	-
	Purchased: Field beans GE	Feedipedia (2012)	Feedipedia (2012)	Normal	18.700	0.200	-	-
	Purchased: Waste vegetables GE	Feedipedia (2012)	Feedipedia (2012)	Normal	17.271	0.141	-	-
	Purchased: Sugar beet pulp GE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***17.000***	***0.500***	-	-
	Purchased: Hay DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***58.100***	***4.728***	-	-
	Purchased: Grass silage DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***60.767***	***2.400***	-	-
	Purchased: Wholecrop cereals DE	Feedipedia (2012)	Feedipedia (2012)	Normal	64.125	5.218	-	-
	Purchased: Maize silage DE	Feedipedia (2012)	Feedipedia (2012)	Normal	68.600	2.300	-	-
	Purchased: Straw DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***45.200***	***3.678***	-	-
	Purchased: Clover silage DE	Feedipedia (2012)	Feedipedia (2012)	Normal	64.700	5.700	-	-
	Purchased: Fodder beet DE	Feedipedia (2012)	Feedipedia (2012)	Normal	84.600	1.600	-	-
	Purchased: Lucerne DE	Feedipedia (2012)	Feedipedia (2012)	Normal	65.500	8.800	-	-
	Purchased: Brewers grains DE	Feedipedia (2012)	Feedipedia (2012)	Normal	63.200	4.700	-	-
	Purchased: Citrus pulp DE	Feedipedia (2012)	Feedipedia (2012)	Normal	83.900	3.400	-	-
	Purchased: Wheat (grain) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	85.700	2.700	-	-
	Purchased: Barley (grain) DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***80.700***	***2.140***	-	-
	Purchased: Oats (grain) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	75.500	3.500	-	-
	Purchased: Potatoes (brock) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.600	-	-
	Purchased: Potatoes (ware) DE	Feedipedia (2012)	Feedipedia (2012)	Normal	87.100	1.600	-	-
	Purchased: Soya meal DE	Feedipedia (2012)	Feedipedia (2012)	Normal	92.200	7.503	-	-

Cat	Name	Coefficient source	Unc'y source	PDF type	Mean/ B.E./ Ln(mean)	Std. Dev.	Min	Max
	Purchased: Rape Meal DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***78.500***	***6.388***	-	-
	Purchased: Distillers Pellets DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***70.900***	***4.700***	-	-
	Purchased: Maize gluten DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***80.400***	***1.500***	-	-
	Purchased: Molasses DE	Feedipedia (2012)	Feedipedia (2012)	Normal	76.600	6.234	-	-
	Purchased: Beef and calf nuts DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***79.196***	***1.740***	-	-
	Purchased: Ewe and lamb nuts DE	Feedipedia (2012)	Feedipedia (2012)	Normal	81.472	2.140	-	-
	Purchased: Dairy and calf nuts DE	Feedipedia (2012)	Feedipedia (2012)	Normal	81.213	1.670	-	-
	Purchased: Milk powder DE	Feedipedia (2012)	Feedipedia (2012)	Normal	83.680	4.184	-	-
	Purchased: Minerals DE	Feedipedia (2012)	Feedipedia (2012)	Normal	0.000	0.000	-	-
	Purchased: Field beans DE	Feedipedia (2012)	Feedipedia (2012)	Normal	89.800	3.000	-	-
	Purchased: Waste vegetables DE	Feedipedia (2012)	Feedipedia (2012)	Normal	83.420	1.700	-	-
	Purchased: Sugar beet pulp DE	***Feedipedia (2012)***	***Feedipedia (2012)***	***Normal***	***80.200***	***4.300***	-	-

A.3. Sample rations utilised in modelling emissions from beef systems

The analyses conducted in chapters four, six and seven of this thesis required modelling hypothetical beef systems. The rations for the animals in these hypothetical systems were defined based on a sample of rations from the literature and provided by personal communication with experts in SAC Consulting. The collated ration sample is provided here (table A.4).

Table A.4. Raw sample of cattle diets used in the derivation of rations for the beef systems described in chapters four, six and seven.

Livestock class	Source	Straw	Hay	Grass silage	Barley (grain)	Rape Meal	Distillers Pellets	Maize gluten	Beef concentrates	Sugar beet pulp	Minerals
		kg fresh weight head^{-1} day^{-1}									
Suckler cow spring calving	HCC Wales (2006)			27.2							0.1
	HCC Wales (2006)	6.2		15							0.1
	HCC Wales (2006)	8.5					2.5				0.1
	HCC Wales (2006)	5						2.5		2	0.1
	K. Stewart (pers. comm.)		9.5			0.6					0.1
	K. Stewart (pers. comm.)	9.8			0.9	1.2		3			0.1
	K. Stewart (pers. comm.)	8									0.1
	K. Stewart (pers. comm.)	9.8				2					0.1
	K. Stewart (pers. comm.)			30							0.1
	K. Stewart (pers. comm.)	4.5		20							0.1
Suckler cow autumn calving	HCC Wales (2006)			40					2		
	HCC Wales (2006)	6						5	3	2	
	HCC Wales (2006)	6						6			0.1
	K. Stewart (pers. comm.)			44	0.75						0.1
	K. Stewart (pers. comm.)			8	3.5						0.1
	K. Stewart (pers. comm.)		13.5		0.6	1.2					0.1
	K. Stewart (pers. comm.)	8.5			5	1.5					0.1
	K. Stewart (pers. comm.)	8.5						6.5			0.1
	K. Stewart (pers. comm.)	8.5					6				0.1
	K. Stewart (pers. comm.)	2	10		2	2					0.1
Growing steer @ 0.6 kg/day	HCC Wales (2006)			20					1.5		0.1
	HCC Wales	4.5					3.5				0.1

	(2006)								
	HCC Wales (2006)	3.5				2.5		1.5	0.1
	HCC Wales (2006)			24			2.5		
Growing steer @ 0.8 kg/day	HCC Wales (2006)	6.5				4.5			0.1
	HCC Wales (2006)	4				5		2	0.1
	HCC Wales (2006)			22			1.5		
Growing heifer @ 0.8 kg/day	HCC Wales (2006)	5.5			4				0.1
	HCC Wales (2006)	3				4.5		2	0.1
	HCC Wales (2006)			34			2		
Growing steer @ 1.0 kg/day	HCC Wales (2006)	8			5				0.1
	HCC Wales (2006)	3.5				5.5		3	0.1
	K. Stewart (pers. comm.)		14				3		0.1
Bull	K. Stewart (pers. comm.)			55			2.5		0.1
	K. Stewart (pers. comm.)			55	10				0.1

A.4. Equations used to link performance parameters for modelled dairy system

The analyses conducted in chapter four of this thesis involved stochastically modelling performance for a hypothetical range of dairy production systems. In order to do this, data from the SAC Farm Management Handbook (SAC, 2016) was utilised to fit regression equations which linked one performance parameter (milk yield) to other, dependent parameters (herd life, calving percentage, cow replacement rate and percentage of concentrate in the ration). This ensured that the stochastic elements of the simulation did not unduly bias the sample. This section presents the parameters fitted to the SAC data (table A.5).

Table A.5. Regression coefficients for equations linking dairy system performance parameters to annual milk yield (in litres).

	Herd life (years)	Calving rate %	Cow rep rate %	LWG kg hd^{-1} day^{-1}	Concentrate in ration % FW
Intercept	7.000	1.102	0.061	0.340	−0.098
Slope	-4.00×10^{-4}	-2.35×10^{-5}	2.64×10^{-5}	5.92×10^{-5}	3.90×10^{-5}
R^2	1.000	0.999	0.976	0.988	1.000

A.5. Raw data for development of the pasture digestibility model

This section of the appendix contains the raw data utilised in the development of the grass digestibility model in chapter five of this thesis. This data took two main forms; estimates of digestibility (DE%) for individual species and mixed swards (table A.6), and estimates of species abundance based on sward management parameters (table A.7).

Table A.6. Estimates of grass species and mixed sward digestibility (DE, as a percentage of gross energy, GE) collated from a review of published literature.

Grass species/ grassland type	Common name	Time period	Digestible energy (% GE)	Source
L. perenne	Perennial ryegrass	May	77.5*	Korevaar (1986) in Bruinenberg et al. (2002)
P. pratensis	Common meadow grass	May	67.8*	Korevaar (1986) in Bruinenberg et al. (2002)
P. trivialis	Rough meadow grass	May	71.1*	Korevaar (1986) in Bruinenberg et al. (2002)
A. stolonifera	Creeping bent	May	66.8*	Korevaar (1986) in Bruinenberg et al. (2002)
A. capillaris	Common bent	May	66.8*	Korevaar (1986) in Bruinenberg et al. (2002)
E. repens	Couch grass	May	71.1*	Korevaar (1986) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	May	71.1*	Korevaar (1986) in Bruinenberg et al. (2002)
R. repens	Buttercup	May	76.4*	Korevaar (1986) in Bruinenberg et al. (2002)
R. acetosa	Sorrel	May	59.3*	Korevaar (1986) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	August	72.1*	Korevaar (1986) in Bruinenberg et al. (2002)
P. pratensis	Common meadow grass	August	65.7*	Korevaar (1986) in Bruinenberg et al. (2002)
A. stolonifera	Creeping bent	August	63.6*	Korevaar (1986) in Bruinenberg et al. (2002)
A. capillaris	Common bent	August	63.6*	Korevaar (1986) in Bruinenberg et al. (2002)
E. repens	Couch grass	August	65.7*	Korevaar (1986) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	August	65.7*	Korevaar (1986) in Bruinenberg et al. (2002)
R. repens	Buttercup	August	76.4*	Korevaar (1986) in Bruinenberg et al. (2002)
R. acetosa	Sorrel	August	75.3*	Korevaar (1986) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	May	79.6*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
P. trivialis	Rough meadow grass	May	75.3*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
A. stolonifera	Creeping bent	May	74.3*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	May	74.3*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
A. geniculatus	Water/marsh foxtail	May	74.3*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	June	67.8*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
P. trivialis	Rough meadow grass	June	61.4*	Korevaar & Van der Wel (1997) in Bruinenberg

Grass species/ grassland type	Common name	Time period	Digestible energy (% GE)	Source
				et al. (2002)
A. stolonifera	Creeping bent	June	65.7*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	June	61.4*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
A. geniculatus	Water/marsh foxtail	June	65.7*	Korevaar & Van der Wel (1997) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	Full year	77.5*	Frame (1991) in Bruinenberg et al. (2002)
P. pratensis	Common meadow grass	Full year	67.8*	Frame (1991) in Bruinenberg et al. (2002)
A. stolonifera	Creeping bent	Full year	67.8*	Frame (1991) in Bruinenberg et al. (2002)
A. capillaris	Common bent	Full year	66.8*	Frame (1991) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	Full year	73.2*	Frame (1991) in Bruinenberg et al. (2002)
F. rubra	Creeping red fescue	Full year	68.9*	Frame (1991) in Bruinenberg et al. (2002)
A. odoratum	Sweet vernal grass	Full year	72.1*	Frame (1991) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	Full year	70*	Frame (1991) in Bruinenberg et al. (2002)
P. pratensis	Common meadow grass	Full year	57.1*	Frame (1991) in Bruinenberg et al. (2002)
A. stolonifera	Creeping bent	Full year	59.3*	Frame (1991) in Bruinenberg et al. (2002)
A. capillaris	Common bent	Full year	53.9*	Frame (1991) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	Full year	64.6*	Frame (1991) in Bruinenberg et al. (2002)
F. rubra	Creeping red fescue	Full year	58.2*	Frame (1991) in Bruinenberg et al. (2002)
A. odoratum	Sweet vernal grass	Full year	60.4*	Frame (1991) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	June	78.5*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
N. stricta	Matgrass	June	59.3*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
M. caerulea	Purple moor grass	June	58.2*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
T. repens	White clover	June	76.4*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	August	64.6*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
N. stricta	Matgrass	August	48.6*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
M. caerulea	Purple moor grass	August	42.2*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
T. repens	White clover	August	58.2*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	October	57.1*	Armstrong et al. (1989) in Bruinenberg et al. (2002)
P. pratensis	Common meadow grass	Full year	63.6*	Buske (pers. comm.) in Bruinenberg et al. (2002)
P. trivialis	Rough meadow grass	Full year	62.5*	Buske (pers. comm.) in Bruinenberg et al. (2002)
A. stolonifera	Creeping bent	Full year	67.8*	Buske (pers. comm.) in Bruinenberg et al. (2002)
E. repens	Couch grass	Full year	70*	Buske (pers. comm.) in Bruinenberg et al. (2002)
H. lanatus	Yorkshire fog	Full year	62.5*	Buske (pers. comm.) in Bruinenberg et al. (2002)
A. geniculatus	Water/marsh foxtail	Full year	73.2*	Buske (pers. comm.) in Bruinenberg et al. (2002)
R. repens	Buttercup	Full year	78.5*	Buske (pers. comm.) in Bruinenberg et al. (2002)
R. acetosa	Sorrel	Full year	50.7*	Buske (pers. comm.) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	April	86.2*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
D. glomerata	Cocksfoot grass	April	80.1*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
P. pratense	Timothy grass	April	84.2*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
T. repens	White clover	April	82.1*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
Mixed grassland		April	83.2*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
L. perenne	Perennial ryegrass	May	80.1*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
D. glomerata	Cocksfoot grass	May	68.9*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
P. pratense	Timothy grass	May	80.1*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
T. repens	White clover	May	80.1*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
Mixed grassland		May	77*	Terry & Tilly (1964) in Bruinenberg et al. (2002)

Grass species/ grassland type	Common name	Time period	Digestible energy (% GE)	Source
L. perenne	Perennial ryegrass	June	69.9*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
D. glomerata	Cocksfoot grass	June	55.6*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
P. pratense	Timothy grass	June	68.9*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
T. repens	White clover	June	77*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
Pasture		June	66.8*	Terry & Tilly (1964) in Bruinenberg et al. (2002)
Pasture		April	69.0	Frame & Laidlaw (2011)
Pasture		May	67.0	Frame & Laidlaw (2011)
Pasture		June	67.0	Frame & Laidlaw (2011)
Pasture		June	62.0	Frame & Laidlaw (2011)
Pasture		July	61.0	Frame & Laidlaw (2011)
Pasture		August	60.0	Frame & Laidlaw (2011)
Pasture		August	61.0	Frame & Laidlaw (2011)
Pasture		September	60.0	Frame & Laidlaw (2011)
Pasture		October	63.0	Frame & Laidlaw (2011)
Mixed pasture & clover		April	74.0	Frame & Laidlaw (2011)
Mixed pasture & clover		May	71.0	Frame & Laidlaw (2011)
Mixed pasture & clover		June	69.0	Frame & Laidlaw (2011)
Mixed pasture & clover		June	64.0	Frame & Laidlaw (2011)
Mixed pasture & clover		July	63.0	Frame & Laidlaw (2011)
Mixed pasture & clover		August	62.0	Frame & Laidlaw (2011)
Mixed pasture & clover		August	63.0	Frame & Laidlaw (2011)
Mixed pasture & clover		September	62.0	Frame & Laidlaw (2011)
Mixed pasture & clover		October	66.0	Frame & Laidlaw (2011)
Pasture	April		79.6**	Dale et al. (2008)
Pasture	May		74.3**	Dale et al. (2008)
Pasture	June		75**	Dale et al. (2008)
Pasture	July		72.4**	Dale et al. (2008)
Pasture	August		70.4**	Dale et al. (2008)
Pasture	September		71.7**	Dale et al. (2008)
Pasture	October		73.7**	Dale et al. (2008)
Pasture	April		73.7**	Dale et al. (2008)
Pasture	May		70.4**	Dale et al. (2008)
Pasture	June		67.8**	Dale et al. (2008)
Pasture	July		67.8**	Dale et al. (2008)
Pasture	August		69.8**	Dale et al. (2008)
Pasture	September		70.4**	Dale et al. (2008)
Pasture	October		69.1**	Dale et al. (2008)
Pasture	April		77**	Dale et al. (2008)
Pasture	May		70.4**	Dale et al. (2008)
Pasture	June		71.1**	Dale et al. (2008)
Pasture	July		70.4**	Dale et al. (2008)
Pasture	August		68.5**	Dale et al. (2008)
Pasture	September		67.8**	Dale et al. (2008)
Pasture	October		74.3**	Dale et al. (2008)

* Value converted from DMD/OMD using regression equations from Rittenhouse et al. (1971).

** Value obtained by converting total metabolisable energy (ME) to digestible energy percentage using a conversion factor of 0.82 (ILCA, 1990) and a gross energy (GE) value of 18.3 (Stergiadis et al., 2015).

Table A.7. Raw abundance data for sown grass species, unsown grass species and white clover (*Trifolium repens*) collated from the literature. Sources are Forbes et al., (1980) and (Swift et al., (1983). Sward age (in years) for data sourced from Forbes et al. was back-translated from an age index using methods described in section A.6.

N	Source	Sward age (years)	N app. rate (kg ha^{-1})	% Sown spp.	% Unsown spp.	% *T. repens*
1	Forbes	17.3425	19	34	66	5.6
2	Forbes	7.2625	137	36	64	0.5
3	Forbes	21.8225	41	44	56	6.8
4	Forbes	21.8225	3	32	68	14.2
5	Forbes	5.53	105.5	56	44	0.3
6	Forbes	10.85	53	50	50	7.9
7	Forbes	11.6725	47	54	46	3.6
8	Forbes	19.5125	79	35	65	3.4
9	Forbes	14.35	35.5	46	54	5.3
10	Forbes	12.53	21	52	48	7.3
11	Forbes	8.5925	58.5	53	47	2.8
12	Forbes	16.31	21.5	30	70	5.9
13	Forbes	20.65	28	19	81	3.2
14	Forbes	17.3425	55.5	35	65	3.5
15	Forbes	16.31	9.5	36	64	7.7
16	Forbes	9.31	12	41	59	4.1
17	Forbes	17.3425	83	36	64	1.8
18	Forbes	19.5125	229	13	87	0.3
19	Forbes	23.03	24	31	69	6.8
20	Forbes	25.55	27	22	78	0.6
21	Forbes	14.35	67.5	34	66	1.4
22	Forbes	9.31	78.5	64	36	7.5
23	Forbes	4.1125	41	68	32	5.1
24	Forbes	17.3425	33.5	46	54	5.3
25	Forbes	8.5925	36	53	47	7.9
26	Forbes	15.3125	62	30	70	5
27	Forbes	10.85	32	47	53	8.6
28	Forbes	16.31	8.5	40	60	4.6
29	Forbes	21.8225	24.5	29	71	5.6
30	Forbes	6.65	89.5	60	40	3.1
31	Forbes	7.91	19	48	52	1.3
32	Forbes	13.4225	78	56	44	2.4
33	Forbes	16.31	82.5	47	53	1.2
34	Forbes	13.4225	26	63	37	4.9
35	Forbes	10.85	82.5	47	53	5.6
36	Forbes	20.65	21.5	37	63	3.5
37	Forbes	9.31	0	52	48	4.7
38	Forbes	21.8225	7	32	68	8.7

N	Source	Sward age (years)	N app. rate (kg ha^{-1})	% Sown spp.	% Unsown spp.	% *T. repens*
39	Forbes	6.0725	54.5	43	57	0.5
40	Forbes	15.3125	161	60	40	1.2
41	Forbes	25.55	69.5	25	75	9.2
42	Forbes	20.65	13	41	59	5.9
43	Forbes	24.2725	6	24	76	8.5
44	Forbes	16.31	49	28	72	1.7
45	Forbes	24.2725	55.5	19	81	3.2
46	Forbes	17.3425	14	37	63	9.9
47	Forbes	25.55	5.5	27	73	0.4
48	Forbes	17.3425	54	28	72	3.1
49	Forbes	11.6725	24.5	31	69	11.6
50	Forbes	21.8225	33.5	22	78	5.6
51	Forbes	25.55	12.5	23	77	3.1
52	Forbes	25.55	51	20	80	2.4
53	Forbes	20.65	46.5	28	72	2.6
54	Forbes	23.03	8.5	12	88	0.4
55	Forbes	20.65	176.5	46	54	0.7
56	Forbes	15.3125	112.5	68	32	3.2
57	Forbes	12.53	77.5	39	61	1.9
58	Forbes	9.31	72.5	59	41	0.6
59	Forbes	20.65	61.5	24	76	2.1
60	Forbes	25.55	30	27	73	2.3
61	Forbes	24.2725	23.5	39	61	7.8
62	Forbes	23.03	18.5	4	96	4.8
63	Forbes	21.8225	56.5	23	77	0.2
64	Forbes	10.85	39.5	49	51	9.9
65	Forbes	11.6725	122.5	56	44	7.8
66	Forbes	17.3425	16	42	58	2.9
67	Forbes	18.41	54	42	58	5.8
68	Forbes	11.6725	16.5	43	57	8.1
69	Forbes	10.0625	67	46	54	2.9
70	Forbes	13.4225	24.5	56	44	12
71	Forbes	10.0625	90	54	46	3.2
72	Forbes	23.03	27	29	71	0.6
73	Forbes	16.31	43	74	26	0
74	Forbes	10.85	15.5	34	66	3.3
75	Forbes	24.2725	32.5	58	42	3
76	Forbes	18.41	35	39	61	7.3
77	Forbes	21.8225	114.5	25	75	2.5
78	Forbes	19.5125	30	39	61	2.3
79	Forbes	7.2625	7.5	53	47	5.3
80	Forbes	6.65	43.5	64	36	6.6

N	Source	Sward age (years)	N app. rate (kg ha^{-1})	% Sown spp.	% Unsown spp.	% *T. repens*
81	Forbes	7.91	35	54	46	3.1
82	Forbes	20.65	14	53	47	4.7
83	Forbes	13.4225	71.5	60	40	2.7
84	Forbes	16.31	53	36	64	4.7
85	Forbes	11.6725	55	52	48	12.8
86	Forbes	16.31	55.5	45	55	6.1
87	Forbes	20.65	4.5	45	55	10.8
88	Forbes	18.41	27	48	52	1.4
89	Forbes	24.2725	22	33	67	9.2
90	Forbes	9.31	13	45	55	4.3
91	Forbes	13.4225	19	50	50	8.7
92	Forbes	16.31	42.5	53	47	7
93	Forbes	12.53	16	48	52	6.5
94	Forbes	14.35	41.5	33	67	0.5
95	Forbes	24.2725	0	28	72	0.3
96	Forbes	9.31	38.5	45	55	1.4
97	Forbes	17.3425	79	33	67	2.5
98	Forbes	19.5125	44	37	63	2.4
99	Forbes	16.31	51	52	48	2.5
100	Forbes	19.5125	23.5	43	57	1.1
101	Forbes	24.2725	21	22	78	1.4
102	Forbes	9.31	8.5	49	51	9.3
103	Forbes	13.4225	9.5	47	53	6.3
104	Forbes	24.2725	13.5	14	86	2.2
105	Forbes	10.85	59	68	32	5.7
106	Forbes	19.5125	50	23	77	2.8
107	Forbes	21.8225	30	22	78	2.6
108	Forbes	10.0625	39.5	30	70	2.3
109	Forbes	19.5125	5.5	19	81	2.7
110	Forbes	15.3125	21	47	53	7.2
111	Forbes	25.55	16	15	85	2.7
112	Forbes	16.31	9	30	70	4.8
113	Forbes	9.31	4.5	40	60	5.7
114	Forbes	14.35	12	20	80	3.8
115	Forbes	25.55	95	28	72	8.5
116	Forbes	10.0625	14	39	61	6.7
117	Forbes	19.5125	1.5	22	78	5
118	Forbes	21.8225	14	23	77	5.8
119	Forbes	21.8225	9	19	81	2.7
120	Forbes	21.8225	44	13	87	1.3
121	Forbes	25.55	12	7	93	0
122	Swift	12	115	73	27	20

N	Source	Sward age (years)	N app. rate (kg ha^{-1})	% Sown spp.	% Unsown spp.	% *T. repens*
123	Swift	3	100	64	36	11
124	Swift	9	102	69	31	13
125	Swift	13	94	74	26	12
126	Swift	10	30	70	30	24
127	Swift	3	182	88	12	2
128	Swift	9	37	68	32	8
129	Swift	3	85	90	10	12
130	Swift	2	260	98	2	13
131	Swift	4	14	95	5	19
132	Swift	18	151	60	40	9
133	Swift	6	0	75	25	22
134	Swift	4	0	79	21	18
135	Swift	4	50	83	17	15
136	Swift	3	0	84	16	15
137	Swift	14	150	93	7	14
138	Swift	11	95	91	9	6
139	Swift	6	45	88	12	14
140	Swift	4	67	92	8	19
141	Swift	9	122	87	13	15
142	Swift	5	0	83	17	22
143	Swift	10	110	91	9	18
144	Swift	17	125	72	28	7
145	Swift	15	125	60	40	10
146	Swift	10	67	84	16	12
147	Swift	20	74	65	35	9
148	Swift	5	59	85	15	15
149	Swift	5	167	86	14	6
150	Swift	25	86	43	57	10
151	Swift	10	65	78	22	15
152	Swift	9	27	71	29	24
153	Swift	11	34	63	37	13
154	Swift	7	0	77	23	23
155	Swift	6	0	55	45	17
156	Swift	10	50	73	27	18
157	Swift	14	125	78	22	14
158	Swift	3	62	95	5	19
159	Swift	11	75	74	26	12
160	Swift	7	64	61	39	13
161	Swift	2	94	93	7	17
162	Swift	8	0	90	10	13
163	Swift	10	55	66	34	15
164	Swift	8	312	94	6	11

N	Source	Sward age (years)	N app. rate (kg ha^{-1})	% Sown spp.	% Unsown spp.	% *T. repens*
165	Swift	6	90	79	21	16
166	Swift	3	312	97	3	14
167	Swift	3	225	88	12	15
168	Swift	13	35	66	34	18
169	Swift	10	35	76	24	11
170	Swift	12	169	76	24	8
171	Swift	12	175	86	14	3
172	Swift	5	45	86	14	24
173	Swift	4	86	83	17	19
174	Swift	5	45	72	28	22
175	Swift	3	250	90	10	3
176	Swift	5	37	91	9	19
177	Swift	8	24	75	25	8
178	Swift	2	295	81	19	5
179	Swift	2	50	94	6	10
180	Swift	11	52	45	55	21
181	Swift	9	116	77	23	8
182	Swift	13	57	49	51	20
183	Swift	9	50	95	5	24
184	Swift	10	75	86	14	14
185	Swift	8	37	75	25	17
186	Swift	3	152	92	8	8
187	Swift	9	137	76	24	8
188	Swift	3	50	90	10	23
189	Swift	17	120	62	38	6
190	Swift	11	29	62	38	20
191	Swift	6	125	90	10	27
192	Swift	12	252	60	40	10
193	Swift	7	47	84	16	20
194	Swift	6	45	89	11	24
195	Swift	10	199	80	20	10
196	Swift	8	104	89	11	9
197	Swift	12	50	62	38	14
198	Swift	6	150	77	23	17
199	Swift	13	72	70	30	12
200	Swift	7	0	86	14	20
201	Swift	4	155	90	10	13
202	Swift	10	75	70	30	18
203	Swift	6	109	81	19	14
204	Swift	3	109	83	17	19
205	Swift	7	62	78	22	16
206	Swift	8	76	65	35	11

A.6. Method for translation of sward age index parameter

Raw spp. abundance data sourced from Forbes et al. (1980) utilised an ‘age index’ parameter in place of an average sward age. To enable use of this data, a method was developed to back-translate this parameter into an estimated sward age, in years. The ‘age index’ method, as described by Forbes et al. (1980), effectively binned data into sward age intervals, as given in table A.8.

Table A.8. Sward age index vs. actual age intervals as defined by Forbes et al. (1980). The mean age of interval was calculated for the purposes of the following regression analysis (Fig. A.1).

Age index	Age range (years)		Mean age of interval (years)
	Min	Max	
1	1	4	2.5
2	5	8	6.5
3	9	20	14.5
4	21	32*	26.5

* The bin for age index [4] was open ended (i.e. had a minimum of 21 years, but no maximum); for the purposes of this exercise, this bin was assigned the range of the next nearest interval (11 years).

Following this approach, a polynomial regression line was fitted to relate the age index to the mean interval age (Fig. A.1).

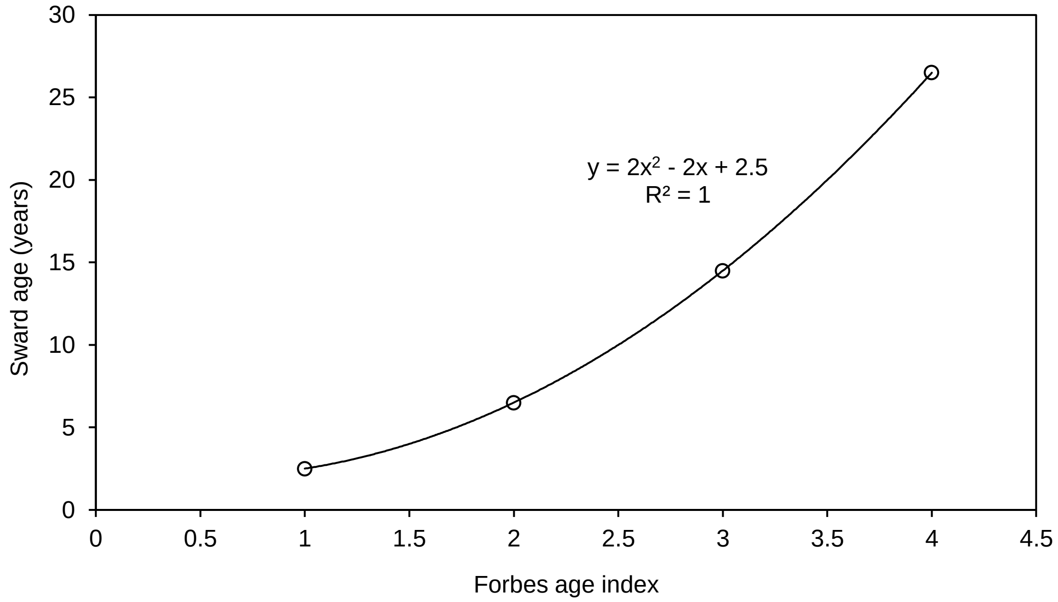

Fig. A.1. Regression line fitted to data from Forbes et al. (1980) to relate the given age index parameter to an estimated sward age in years.

The following (equation A.5) could then be utilised to convert the sward age index, as given by Forbes et al. (1980), into an estimated sward age for the purposes of the model processes described in chapter five of this thesis.

Equation A.5. Polynomial conversion of sward age index (dimensionless) into sward age (in years).

$$S_{age} = 2 \cdot {S_i}^2 - 2S_i + 2.5$$

Where:
S_{age} = estimated sward age, in years
S_i = sward age index parameter (dimensionless) as defined by Forbes et al. (1980)

A.7. Quantities measured and modelled

This appendix section provides a reference list of all quantities derived, measured and modelled in this thesis. For brevity, this has been split into generally recognised quantities (table A.9) and quantities specific to the modelled approaches derived in this thesis (remainder of section).

Table A.9. Generally recognised quantities used throughout this thesis (alphatbetised).

Quantity	Description	Unit(s) used
CH_4	Methane	g, kg
CO_2-eq	Carbon dioxide equivalents	g, kg
DE(%)	Digestible energy (percentage). Where given as a percentage this refers to a percentage of gross energy (GE).	MJ, % GE
DM	Dry matter weight (of grass or ration component)	kg
GE	Gross energy	MJ
hd	Head (of livestock), one head indicating one individual.	n/a
LW	Animal live weight	kg
LWG	Live weight gain	kg hd^{-1} day^{-1}
N_2O	Nitrous oxide	g, kg
$NE_{(m/a/g/p/l)}$	Net energy (subscript indicating for maintenance, activity, growth, pregnancy, and lactation respectively)	MJ

The remainder of this section comprises an alphabetised list of all quantities defined and modelled in this thesis. Note that, for brevity, this list does not overlap with the PDFs defined in table A.2.

$CH_{4\ enteric}$ = Enteric methane (in kg or kg CO_2-eq, as specified in text)
$CP\%_{grazed}$ = the CP% of grazed grass (as a % of DM)
$CP\%_{pasture}$ = the CP% of the diet at pasture (final model input)
$CP\%_{supp}$ = the CP% of supplementary feed (as a % of DM)
$DE\%_{final}$ = weighted digestibility % of the overall diet
$DE\%_{grazed}$ = digestibility of grazed grass, (as % of GE)
$DE\%_{housed}$ = digestibility % of the housed ration
$DE\%_{pasture}$ = digestibility % of the diet at pasture
$DE\%_{pasture}$ = the overall DE% of the diet at pasture (as % of GE)
$DE\%_{ration}$ = the DE% of the ration overall
DE_{req} = animal digestible energy requirements (MJ hd^{-1} day^{-1})
DE_{req} = modelled animal digestible energy requirements (MJ hd^{-1} day^{-1})
DE_{supp} = digestible energy supplied by supplementary feed, in (MJ hd^{-1} day^{-1})
DE_x = the DE% of ration component x
DM_{grazed} = the DM intake from grazing, (kg)
DM_{sup} = the DM intake from supplementary feed (kg)
DM_x = the dry matter % of ration component x
$Frac_{lolium}$ = Fraction of *L. perenne* in sward (as a fraction of total sward cover)

$Frac_{other}$ = Fraction of other sown spp. in sward (not including *L. perenne*) (as a fraction of total sward cover)
$Frac_{sown}$ = Fraction of sown spp. in sward (inc. *L. perenne*) (as a fraction of total sward cover)
$Frac_{trifolium}$ = Fraction of T. repens in sward (as a fraction of total sward cover)
$Frac_{unsown}$ = Fraction of unsown spp. in sward (as a fraction of total sward cover)
$Frac_x$ = the fresh weight (FW) fraction of component *x* in the ration
GE_{grazed} = GE supplied by grazed grass (MJ)
GE_{grazed} = GE supplied by grazed grass (MJ)
GE_{supp} = GE supplied by supplementary feed (MJ)
GE_x = the GE (in MJ kg DM^{-1}) of ration component *x*
Lolium % = Calculated percentage of *L. perenne* in sown grasses (as a % of sown grass abundance)
NE_a = net energy for animal activity (MJ hd^{-1} day^{-1})
NE_g = net energy needed for growth (MJ hd^{-1} day^{-1})
NE_l = net energy for lactation (MJ hd^{-1} day^{-1})
NE_m = net energy required by the animal for maintenance (MJ hd^{-1} day^{-1})
NE_p = net energy required for pregnancy (MJ hd^{-1} day^{-1})
N_{rate} = N fertiliser application rate (kg ha^{-1})
REG = ratio of net energy available for growth in a diet to digestible energy consumed (dimensionless)
REM = ratio of net energy available in a diet for maintenance to digestible energy consumed (dimensionless)
S_{age} = Sward age since reseeding (years)
T_{housed} = time housed, as a fraction of the total year
$T_{pasture}$ = time at pasture, as a fraction of the total year

A.8. Acronyms, initialisations and abbreviations

All acronyms, initialisations and abbreviations utilised in this thesis are presented this appendix section A.8.

AERU	Agribusiness and Economics Research Unit (Lincoln University, New Zealand)
AGWP	Absolute Global Warming Potential
ALW	Average Live Weight
AN	Ammonium Nitrate
ANOVA	Analysis of Variance
AP	Ammonium Phosphate
BE	Best Estimate
BSI	British Standards Institute
CALM	Carbon Accounting for Land Managers (GHG accounting tool)
CAN	Calcium Ammonium Nitrate
CCaLC	Carbon Calculations over the Life Cycle of Industrial Activities (GHG accounting tool)
CDI	Centre for Dairy Information
CFF	Climate Friendly Food (GHG accounting tool)
CFT	Cool Farm Tool (GHG accounting tool)
CH_4	Methane
CI	Confidence Interval
CLA	Country Land and Business Association
CO_2	Carbon Dioxide
CP	Crude Protein
CPLAN	CPLAN GHG accounting tool
CW	Carcass Weight
DA	Disadvantaged Area
DAP	Diammonium Phosphate
DE	Digestible energy
DECC	Department of Energy and Climate Change (United Kingdom Government)
DEFRA	Department of the Environment, Farming and Rural Affairs (United Kingdom Government)
DF	Degrees of Freedom
DLWG	Daily Live Weight Gain
DM	Dry Matter
EBLEX	English Beef and Lamb Executive
EF	Emission Factor
EI	Emissions Intensity
ERSA	Economic Report on Scottish Agriculture
EU	European Union
FAO	Food and Agriculture Organisation of the United Nations
FCAT	Farm Carbon Assessment Tool (GHG accounting tool)
FW	Fresh Weight
GDP	Gross Domestic Product
GE	Gross Energy
GHG	Greenhouse Gas
GIS	Geographic Information System
GTP	Global Temperature change Potential
GWP	Global Warming Potential
HCC	Hybu Cig Cymru
HSD	Honest Significant Difference
IBERS	Institute of Biology, Environmental and Rural Sciences (University of Aberystwyth)
ILCA	International Livestock Centre for Africa
INRA	Institut National de la Recherche Agronomique
IPCC	Intergovernmental Panel on Climate Change
JHI	James Hutton Institute
LCA	Life Cycle Assessment
LFA	Less Favoured Area
LUC	Land Use Change
LULUC	Land Use and Land Use Change
LW	Live Weight
LWG	Live Weight Gain
MAFF	Ministry of Agriculture, Fisheries and Food
MAP	Monoammonium Phosphate

MCA	Multi-Criteria Analysis
MCF	Methane Conversion Factor
MCS	Monte Carlo Simulation
ME	Metabolisable Energy
MJ	Megajoules
MOP	Muriate of Potash
MS	Microsoft
MSE	Mean Square Error
NE_m	Net Energy for Maintenance
NE_a	Net Energy for Activity
NE_g	Net Energy for Growth
NE_l	Net Energy for Lactation
NE_p	Net Energy for Pregnancy
NH_3	Ammonia
NK	Nitrogen-Potassium (fertiliser)
N_2O	Nitrous Oxide
NPK	Nitrogen-Phosphate-Potassium (fertiliser)
NZ	New Zealand
OJEC	Official Journal of the European Union
OLS	Ordinary Least Squares
OMD	Organic Matter Digestibility
PAS2050	Publicly Available Specification 2050
PDF	Probability Density Function
PK	Phosphate-Potassium (fertiliser)
PLC	Public Limited Company
PMF	Probability Mass Function
PO_4^{3-}	Phosphate
PRP	Pasture, Range and Paddock
QMS	Quality Meat Scotland
RCP	Representative Concentration Pathway
REG	Ratio of Energy for Growth
REM	Ration of Energy for Maintenance
RESAS	Rural and Environment Science and Analytical Services (division of Scottish Government)
RSD	Relative Standard Deviation
SAC	Scottish Agricultural College
SO_4	Sulphate
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SRUC	Scotland's Rural College
TSP	Triple Super Phosphate
UAN	Urea-Ammonium Nitrate
UK	United Kingdom
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
VBA	Visual Basic for Applications